QUANTIFICATION OF TERRESTRIAL CARBON STOCKS -A COMPARATIVE LITERATURE SURVEY

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Tiivistelmä – Referent - Abstract

Ihmisen toiminta on vaikuttanut hiilen kiertokulkuun. Maalla sijaitsevien hiilivarastojen koko on pienentynyt, kun samaan aikaan ilmakehän hiilidioksidipitoisuus on kasvanut aiheuttaen ilmaston lämpenemistä. Pariisin ilmastosopimuksen tavoite on rajoittaa lämpeneminen alle 1,5 asteeseen ja tähän tavoitteeseen pääsemiseksi tarvitaan useita eri keinoja. Yksi mahdollinen keino on hiilensidonta maaperään ja kasvillisuuteen. Jotta luonnolliset hiilivarastot saadaan tehokkaasti mukaan EU -politiikkaan, tulee varastoihin sitoutuneen hiilen määrä pystyä kvantifioimaan. Kehittyviä hiilimarkkinoita varten menetelmän tulee olla tarkka, käytännöllinen ja taloudellisesti mahdollinen.

Tämän tutkimuksen tutkimusmenetelmä oli vertaileva kirjallisuuskatsaus ja tavoitteena oli kerätä ja vertailla tietoa tällä hetkellä käytössä olevista menetelmistä hiilen varastojen koon määrittämiseen.

Maaperän hiilivarastojen koko pystytään kvantifioimaan maaperänäytteillä, erilaisten maaperäantureiden ja mallinnuksen avulla. Kasvillisuuteen sitoutuneen hiilen määrää voidaan kvantifioida inventaarioperusteisesti tai kaukokartoituksen avulla. Koko ekosysteemin hiilibudjetti saadaan määritettyä kaasuvuo mittauksilla. Maaperän ja kasvillisuuden hiilivarastojen koon ja varaston muutoksen määrittäminen ei ole yksinkertainen tehtävä. Varastojen välillä on runsaasti vaihtelua ja varastoissa tapahtuvat muutokset ovat osittain erittäin hitaita. Varastojen koon määrittämisen kustannukset vaihtelevat tarkkuuden, varaston koon ja toimenpiteiden mukaan. Menetelmät ovat myös riippuvaisia hyvälaatuisesta tiedosta, minkä vuoksi erilaiset tutkimukset hiiliensidontaan vaikuttavista tekijöistä ovat välttämättömiä.

Tällä hetkellä hiilimarkkinoita ajatellen erilaiset mallinukseen pohjautuvat menetelmät ovat kustannustehokkaita, läpinäkyviä ja toistettavia, minkä vuoksi niitä voitaisiin hyödyntää jo nyt. Ei ole kuitenkaan olemassa täydellistä mallia, eikä yhtä vaihtoehtoa kaikkiin tilanteisiin, minkä vuoksi eri mallien toiminta tulee olla todennettua. Tämän lähestymistavan myötä voisi kuitenkin olla mahdollista saada enemmän pieniä toimijoita hiilensidonnan markkinoille ja siten tehostaa ilmastotoimia.

Eri menetelmät tuovat erilaista tietoa ja myös mallinnukseen pohjautuva lähestymistapa on riippuvainen empiriasta, minkä vuoksi olisi tärkeää, että kaikki informaatio saadaan hyödynnettyä menetelmien kehittämisessä ja tarkkuuksien parantamisessa.

Avainsanat — Nyckelord — Keywords

Hiilivarastot, hiilensidonta, maaperän orgaaninen hiili, biomassa, mittausmenetelmät

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Tiivistelmä — Referat — Abstract

The natural carbon cycle is affected by human activity. Terrestrial carbon stocks have been decreasing as at the same time carbon dioxide concentration in the atmosphere has increased causing climate change. The Paris Agreement sets the target to limit climate change to 1.5°C and to reach that goal, all possible mitigation practises should be included into global framework to avoid the most serious consequences of warming. Carbon sequestration into natural soil and biomass could be one mitigation practice. To enhance carbon sequestration activities and to include natural carbon stocks into to the EU climate policy, it would be necessary to quantify stock sizes and changes in those stocks. For developing carbon trading markets, the quantification methods should provide accurate results and at the same time be practical and financially achievable.

Used research method in this thesis was comparatively literature survey and aim was to gather and compere information about currently used carbon stock quantification methods against developing carbon trading markets.

Soil carbon stocks can be quantified with direct soil sampling, spectroscopic sensing methods or by mathematical models. Biomass carbon stocks can be quantified with inventory-based field measurements and modelling and by remote sensing. The full carbon budget on the ecosystem level can be achieved with carbon flux measurements.

Quantification of different terrestrial carbon stocks and their changes is not a simple task. There is a lot of variation between different stocks and in some cases, the stock changes occur slow. Cost of carbon stock quantification depends on the accuracy, size of the area under focus and frequency of the measures. Methods for terrestrial carbon stock quantification are dependent on high quality data and there is demand for research considering carbon sequestration.

For carbon offsetting purposes of developing carbon markets, the modelling approach is achievable, cost efficient, repeatable and transparent. There is no perfect model or one universal model that would fit to every situation and thus the differences must be known. At this stage, this approach could be one possibility to include small scale projects and enhance climate actions.

Different quantification methods provide information which can be used to different method developments and to increase accuracies. It’s important to know, how all information can be effectively utilized.

Avainsanat — Nyckelord — Keywords

Carbon stocks, carbon sequestration, soil organic carbon, biomass, measurement

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1 Introduction

The natural carbon cycle is affected by human activity, and terrestrial carbon pools have been decreasing. At the same time carbon concentration in the atmosphere and oceans has increased (Ciais et al. 2013, Sanderman et al. 2017). Disturbance of this natural cycle causes different negative impacts to current state of global climate and the states of the oceans. Carbon dioxide (CO_2) is responsible for the majority of global warming, but methane (CH_4), nitrous oxide (N_2O) and volatile organic compounds (VOCs) all are issues of concern (Toensmeier 2016). The concentration of these greenhouse gases (GHG) has increased in the atmosphere since industrialization. The use of fossil fuels as a source of energy, land use and changes in land use are the major causes of these rapidly elevated concentrations. CO_2 concentration has increased by 40% from 1750 to 2011, CH_4 150% and N_2O 20% in same time period (Ciais et al. 2013).

Terrestrial carbon locates naturally in soils and in biomass. Carbon pool in soils is twice as large as that in atmosphere (Smith 2012). Thus, even small changes in this stock can influence the atmospheric CO_2 concentrations. Biomass carbon stock size is approximately the same as the atmospheric pool (Smith 2012). Carbon in soil and biomass can be released into the atmosphere due to the burning of fossil carbon, land use changes, management practises or because of natural causes due to the decomposing of organic matter (Janzen 2004). Soil carbon stocks are especially important because they can sequestrate large amounts of atmospheric CO_2, which makes soil important factor to the global carbon balance (Bispo et al. 2017). Land is needed for food production and living space, and because population and per capita consumptions increases, demand for food and natural resources also grow continuously. This creates consequent stress to ecosystems. Global land use changes include for example deforestation and expansion of agriculture in tropics, afforestation and reforestation in temperate regions, intensification of agriculture and urbanization. The vegetation cover has been lost in many arid and semi-arid ecosystems in all climate domains (Song et al. 2018).

The Paris Agreement (2015) sets the target to limit climate change to 1.5°C. To reach that goal, all possible mitigation practises should be included into the global framework to avoid climate change. Carbon sequestration into natural pools could be a strategy for the

removal of greenhouse gases from the atmosphere. Carbon sequestration is also called negative emission technology or carbon dioxide removal option (Smith 2016). Climate, land use, management and edaphic factors affect the amount of carbon stocks, but changes in those pools are not well understood. Without appropriate understanding it's hard to design monitoring, reporting and verification platforms (Smith et al. 2020). Carbon sequestration is also a reversible process so long-term monitoring is necessary to ensure that carbon sequestrated persisted in these pools (Smith 2012). In this thesis, I'm only considering carbon sequestration through biological processes.

Greenhouse gas emissions and carbon stocks are complex to measure. Climate, soil and vegetation characteristics and land management practises cause variation and large heterogeneity in carbon emissions and stocks. These factors vary largely in all spatial scales (Bispo et al. 2017). Terrestrial carbon pools have climate change mitigation potential with low associated costs (Elofsson and Gren 2018). To include these pools to EU climate policy, it would be necessary to quantify the carbon stock sizes and changes in stocks. For market confidence and to satisfy regulatory requirements the quantification methods should provide accurate results and at the same time being practical and financially achievable (Roxburgh et al. 2015). Measuring and monitoring of stocks is a key step towards sustainable carbon markets (Lankoski et al. 2020).

2 Research objectives and method

Purpose of this thesis is to gather information about currently used terrestrial carbon stock quantification methods. Under interest were especially uncertainties, accuracy, costs and scale associated to different methods. One important factor is also the complexity of the method, which affects the expertise requirements. The aim was to compare the usability of different methods against developing carbon trading markets, because carbon offsetting projects need cost-effective and achievable carbon stock and stock change quantification method. Research questions are:

1. How can the size of biomass and soil carbon pools be determined?
2. Pros and cons of different carbon pool estimation methods as tool of carbon emission trading/carbon offsetting?

Used research method in this thesis was comparatively literature review. Scientific articles were collected from Helsinki University Library's Helka information research portal and Google Scholar literature research tool. Article search was conducted according to keywords, which included: carbon stock, biomass stock, measuring, estimation, accuracy, cost, uncertainties, quantification method. Discovered literature was evaluated based on the scientific credibility and content. Scope was in a forest and agricultural land use types.

3 Background

3.1 Carbon in terrestrial ecosystems

There are five major carbon (C) pools in the Earth (Fig. 1): Ocean (77.4% of global carbon pool), fossil carbon (14.9%), soil (5%), biotic pool (1.2%) and atmospheric pool (1.5%). These pools are not constant but carbon cycles back and forth between them. Carbon cycle is a natural planetary cycle and it has occurred billions of years (Toensmeier 2016). Carbon's natural cycle has been affected by human actions: the amount of fossil carbon is decreasing annually due to the burning of fossil fuels, soil carbon pools has reduced since the start of industrialization because of land use management, and the same human activities have also decreased the size of the biotic pool (Ciais et al. 2013). The atmospheric carbon increases because the other pools decrease, and the amount of carbon in oceans grow annually because it partially absorbs the excess carbon from the atmosphere (Ciais et al. 2013, Toensmeier 2016).

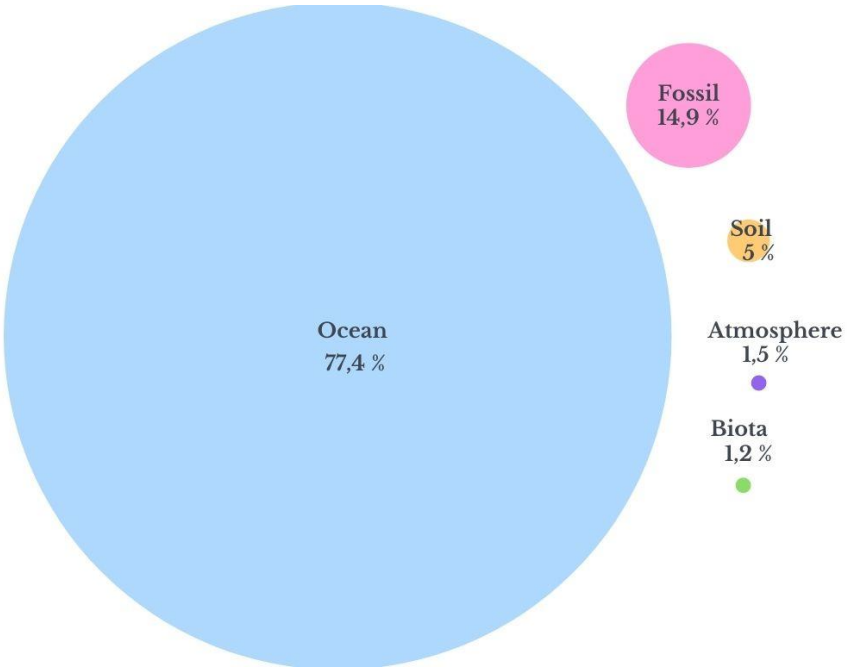

Fig. 1. Illustrative picture of relative sizes of the different carbon pools on Earth.

Soil and biotic carbon are terrestrial carbon pools. Biotic carbon pool means living biomass, plants and animals, and dead detritus. Deforestation and agriculture have caused the loss of terrestrial carbon, the estimated loss amount is 320 billion tons of carbon, and majority of this has happened since 1850 (Ciais et al. 2013, Smith 2012, Toensmeier 2016). The excess carbon in the atmosphere causes global warming due to greenhouse gas effect, but soil degradation and loss of biotic pool have also other, complicated negative effects. Soil degradation have caused e.g. problems with soil fertility and erosion, especially in areas with intense soil use (Wild 1993). Loss of biodiversity is also well recognized problem (Dirzo and Raven 2003).

According to Jobbagy and Jackson (2000), the first three meters of mineral soils contain between 1500 and 2400 Pg of organic carbon. They estimated that first meter contains globally approximately 1500 Pg carbon, second and third meter 490 and 350 Pg carbon, respectively. Terrestrial vegetation contains approximately 450–650 Pg of carbon. Peat soils and permafrost account for more than 1500 Pg. These carbon pools are distributed across the terrestrial ecosystems (Fig. 2).

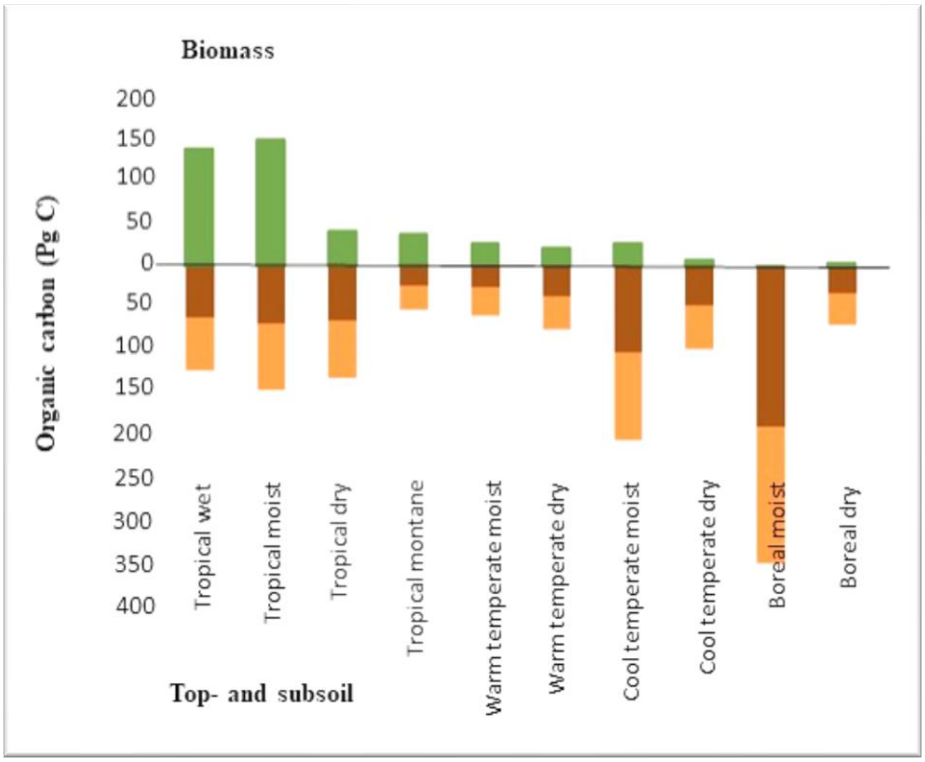

Fig. 2. Organic carbon pool sizes in different climatic regions. Green bars present above- and belowground biomass carbon. Topsoil (brown) and subsoil (orange) present the soil organic carbon pools. It's notable that terrestrial organic carbon pools are not distributed evenly across different climatic regions. Modified from Scharlemann et al. (2014).

3.2 Carbon cycle of atmosphere-plant-soil ecosystems

Terrestrial carbon pools interact constantly with atmospheric carbon via photosynthesis and respiration (Fig. 3). Trough photosynthesis, plants convert sunlight, water and atmospheric carbon dioxide (CO_2) into carbohydrates and oxygen. This photosynthesized carbon, which plant use for growth, creates the biomass carbon pool, or biomass carbon stock (Taiz and Zeiger 2010). According to Toensmeier (2016) carbon that plants do not use directly can be transported to soil. Photosynthetic carbon is transported into the soil from plant roots as compounds that plant roots exude. There are more than 200 carbon-rich compounds that plants produced for different purposes (Taiz and Zeiger 2010). These exudates' roles include e.g. helping with nutrient cycling by feeding soil organisms, functioning as a suppressor of diseases, or to entice predators of pests (plant-microbe interaction in rhizosphere). Between 10 and 40% of photosynthesized carbon passes though the roots within an hour (Taiz and Zeiger 2010, Toensmeier 2016). Over time,

plants die, and aboveground biomass falls to the ground, where carbon-rich litter is partly decomposed. In this process, about 60–70% of carbon is released into the atmosphere as CO_2, and the remaining becomes soil organic matter (SOM) (Toensmeier 2016). Dead root biomass can become soil carbon as well. About half of soil organic matter is carbon (SOC). Respiration is the opposite reaction of photosynthesis and it describes the carbon flux form the soil to the atmosphere. Respiration can be divided into autotrophic respiration, which means carbon dioxide flux from plants, and heterotrophic respiration which refers to respiration of soil fauna. Rate of respiration and rate of photosynthesis depends from several environmental, climatic, soil characteristic and species-specific factors (Raich and Nadelhoffer 1989).

Carbon balance describes the balance of photosynthesis and plant and soil respiration (Fig. 3). If rate of photosynthesis is higher than total respiration rate, the ecosystem stores more carbon than it emits. These total fluxes determine, if the soil and biomass are carbon sinks and potential long-term carbon pools. Globally the annual flux of carbon between decomposition of organic matter and plant respiration is 119.7 Pg and photosynthesis flux is 123 Pg carbon per year, which makes soil a carbon sink (Bispo et al. 2017).

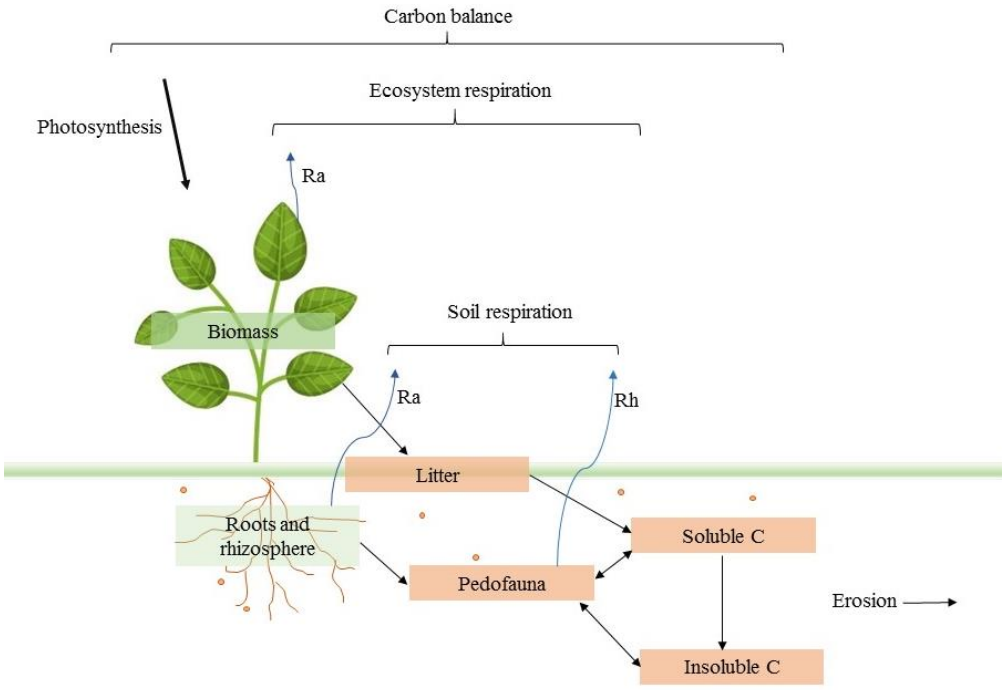

Fig. 3. Simplified chart picture presenting carbon cycle between atmosphere and terrestrial ecosystem. Arrows present the carbon transport between different carbon soil and biomass pools. Modified from Nordblad 2019.

3.3 Biomass carbon

Plants sequester carbon within their biomass. Biomass carbon pools are aboveground and belowground biomass (IPCC 2006). Some of the synthetized glucose from photosynthesis is used for plant growth. Cellulose and lignin are important parts of plant cell wall and they are the backbone of plants providing structure and support. Cellulose and lignin have high carbon content and approximately 50% of the weight of the dehydrated plant biomass is carbon (Taiz and Zeiger 2010, Sedjo and Sohngen 2012).

3.4 Factors affecting biomass carbon pools

When plant sequestrates carbon and produces glucose, it enables the growth, and larger growth means also higher photosynthesis rate. Net carbon uptake is highest in forests when the stands is closed and reasonably young (Sedjo and Sohngen 2012). Plant growth depends on temperature, radiation, moisture and nutrients and demand of these basic variables is species specific (Taiz and Zeiger 2010). In well balanced growth conditions, plant can achieve species specific maximum growth rate. Plant age, disturbances, climate and nutrient availability are the main controllers of plant productivity (Magnani et al. 2007). Nutrient availability is major growth limiting factor in several ecosystems (LeBauer and Treseder 2008).

Because carbon sequestration is a reversible process, photosynthesized carbon can be released back to the atmosphere in respiration (Taiz and Zeiger 2010). Decomposition rate is highly dependent on temperature and moisture and it occurs mainly in soil (Lukac and Godbold 2011). Decomposition process is described with more detail in soil carbon section below.

Other important factors decreasing biomass carbon pools are harvesting, fires and herbivory (Sedjo and Sohngen 2012). Harvesting is the main factor affecting the amount of biomass carbon stocks. The manner of how harvested products are used determines the permanence of carbon. Harvested crops and trees that are used for short-lived products releases the carbon quickly back to the atmosphere. Trees can also be used to produce long-term products, which bind the carbon until wood starts to decay (Pukkala 2019).

Fires (Fig. 4) and herbivory affect the amount of biomass. For example, in 2008, 189.7 Tg of CO_2 was released into the atmosphere from fires in US (Sedjo and Sohngen 2012).

Fig. 4. Boreal forest after a small wildfire. Ground was covered with few centimetres' depth layer of charred plant material and dead needles. Photo: Anniina Lampinen.

3.5 Soil organic carbon

Soil organic matter includes all organic components in the soil, and it is a complex mixture of compounds (Wild 1993). Litter is the first stage of organic matter entering the soil. Litter is dead plant material and it can origin from aboveground (canopy) or belowground (roots) (Lukac and Godbold 2011). Litter is full of nutrients and energy and their accessibility depends on the quality of litter. Litter quality can be estimated with its ratio of total carbon to total nitrogen (C: N) (Lukac and Godbold 2011).

Soil organic matter carbon content varies from 40-67% (FAO 2019). Soil carbon can be divided into soil organic carbon (SOC) and soil inorganic carbon (SIC). Soil inorganic carbon comprehends mainly carbonate minerals calcite ($CaCO_3$) and dolomite [$CaMg(CO_3)_2$] and they are from geologic sources. Soil organic carbon is the carbon component of organic matter (SOM) (Lorenz and Lal 2018). According to Killham and Foster (1994) soil organic carbon can be separated into three pools: soluble, insoluble and biomass. Soluble fraction's decomposition rate is fast and because of that, soils consists only of 1% of soluble carbon. 90% of soil carbon is insoluble and it is a complex mixture of different plant materials in different decomposition states. Insoluble organic carbon forms the SOC stocks. Soil biomass (9%) comprehends soil microbes and animals which are responsible for most of the decomposition activity and carbon cycle (Killham and Foster 1994). Stabile carbon is formed when carbon interact with soil particles (Killham and Foster 1994). Because soil organic matter comprehends a variety of different chemical compounds (Wild 1993), it interacts with soil's mineral particles resulting in organo-mineral associations. Soil aggregates are one result from this interaction, and they are an important factor affecting soil carbon stability. Small humified compounds have high affinity for clay particles, and more than half of the total soil carbon is strongly bound to clay. This strong bond increases significantly the residence time of carbon in soils (Lukac and Godbold 2011).

3.6 Factors affecting soil organic carbon pools

Soil organic matter accumulation and distribution is affected by several biotic and abiotic factors and processes. Biotic factors include plant input and soil organisms. Important abiotic factors are e.g. climate (temperature and precipitation) and soil mineralogy (soil physio-chemical properties) (Luo et al. 2017). Anthropogenic factors have also an impact to soil carbon accumulation and distribution. Typical land management practises like fertilization with nitrogen and tillage affect to soil microorganism and structure (Jackson et al. 2017, Lorenz and Lal 2018). Soil organic carbon stocks are a result of complex interactions among several variables (Lukac and Godbold 2011).

Litter is mainly decomposed via biological processes. Soil microbes and other living organism produce enzymes and metabolic substances which drive the decomposition processes. Activity of those enzymes are temperature and moisture limited, and each have

specific optimal range (Boyero et al. 2011). Soil microbes use carbon for growth and release it via respiration. When microbes die, these microbial residues or so called necromass, can be recycled as new substrates or it can be stabilized. Stabilization happens after necromass is bound to soil mineral surfaces and stored as microaggregates (Miltner et al. 2011). According to Kallenbach et al. (2016) and Balser and Lian (2011) 50-80% of stable organic carbon in soils is necromass. Environmental and microbial controls, which are important factors controlling necromass recycling and thus soil carbon stabilization (Buckeridge et al. 2020).

Aboveground biomass sequestrates carbon from the atmosphere and higher plant productivity often increases SOM in the soils. The relationship between net primary production (NPP) and SOC accumulation is not linear and bigger biomass does not automatically lead to increase in SOC pools (Jackson et al.2017). Reasons for these nonlinear relationships are not well known because soil complex interactions and processes are not yet well understood. Some of the suggested reasons are soil carbon saturation (Mayzelle et al. 2014), the priming effect (Kuzyakov 2010) and carbon allocation between plant parts (Jobbagy and Jackson 2000). Soils have limited capacity to sequester carbon and they can saturate. The level of soil carbon saturation varies, and it's affected e.g. by soil minerology and climate (Mayzelle et al. 2014). The priming refers to a situation where plant input to soil increases microbial activity which leads to losses of accumulated SOM (Kuzyakov 2010). Carbon allocation between above- and belowground biomass can also be one of the factors explaining the nonlinear relationship between carbon input and SOC accumulation. Different plant species in diverse environments distribute carbon compounds differently between plant parts. The allocation of net primary productions patterns varies between species and ecosystems, such ranging from 10% of carbon is allocated to roots in croplands, to 60% in native grasslands and 20% in forests (Poorter et al. 2012).

Carbon is not evenly spread in soil profile. Different soil layers typically include different amounts of carbon and this vertical variability is due the different decomposition rates of organic matter and their transportation. Vegetation has also impact and deep rooting vegetation can potentially store carbon into deeper soil layers (Jobbagy and Jackson 2000).

At the landscape scale, soil texture, pH, mineralogy, topology and land-use are the main factors affecting SOC heterogeneity. At the plot scale, plant species diversity and composition, and land management practises increase SOC heterogeneity (FAO 2019). Soil pH, clay content and cation exchange capacity all affect soil biochemical composition and distribution. These factors vary greatly on the ecosystem level but also on a smaller scale. Agricultural lands are relatively homogeneous compared to forests, but even in arable soils, where nitrogen deposit, pH and clay content are usually well monitored, spatial variation occurs on the farm level (Bispo et al. 2017).

3.7 Practices to promote carbon sequestration

Increasing the carbon input and decreasing the decomposition is the basic of carbon accumulation. Net primary production and decomposition rate varies between sites naturally, but there are management practises that are known to affect positively to the size of the different carbon stocks in forests and cultivated soils. Different agricultural and forestry practises e.g. residual management, soil tillage and fertilizer application add variation to carbon accumulation (Bispo et al. 2017). Global forest annual carbon sequestration potential is estimated to be 2-4 Gt C of atmospheric carbon. The “4 per mille Soils for Food Security and Climate” is an act which was launched to increase soil organic carbon content by 0.4% per year and at the same time to mitigate climate change. The 4p 1000 Iniative was a result from global survey where soil organic pool sizes and sequestration potentials were estimated. They reported that under best management practises 0.4% sequestration rate would be accomplished in cultivated soils in areas where topsoil carbon content is low, less than 30 t C/ha. With this rate, global agricultural lands would be able to sequester 2-3 Gt carbon annually, which would offset 20-33% of anthropogenic emissions (Minasny et al. 2017).

In arable land, management practices and history of those affect the accumulation. Conservation practices have a technical potential to increase the soil carbon stocks (Lorenz and Lal 2018). Globally applied conservation principles include minimizing soil disturbance, maximizing surface cover and stimulate biological activity through cover crops, crop rotation and integrated nutrient and pest management (Lorenz and Lal 2018). Term regenerative farming is nowadays commonly used term to describe those

management practices that aim to minimize erosion and leaching of nutrients and organic matter, enhance biodiversity and soil health and to sequester carbon (Elevitch et al. 2018).

Tillage management, crop rotation, agroforestry, cover crops and application of organic amendments are land management practices that could increase carbon concentration in soils (Karhu et al. 2012, Poeplau and Don 2015, Paustian et al. 2016, Brekke et al. 2019). For example, tillage of soil produces more CO_2 efflux than soils that are under no-tilled soil management, which is partly due the fact that tillage makes soil organic material available to oxidation and microbial mineralization (Brekke et al. 2019, Peterson et al. 2019). Haddaway et al. (2017) concluded that SOC accumulated to topsoil layer (depth 0-30 cm) under no-tillage and intermediate intense tillage practices, but SOC accumulation was not noticed in whole soil profile. Selection of crop variate and avoiding the use of bare fallows have also positive impact to soil carbon accumulation (Lorenz and Lal 2018). Cultivation of cover crops increases the soil carbon accumulation by 32 g C/m^2 ($R^2 = 0.17$) annually (Poeplau and Don 2015) and they also prevent nutrient leaching and are beneficial to soil (Dabney et al. 2001). Higher plant species richness is also shown to increase SOC storages in mineral soils for example due to increase of microbial biomass and necromass (Prommer et al. 2019).

Afforestation is one way to increase the amount of terrestrial biomass carbon. Tree and other vegetation growth in previously unforested sites would also increase the amount of carbon in soils (Sedjo and Sohngen 2012). Peltoniemi et al. (2004) studied how growing stands (afforested site) would affect the soil carbon accumulation and they found out that carbon stock increased average of 4.7 ± 1.4 g/m^2/year with increasing stand age. This accumulation was only noticed in organic layers, and no significant changes were measured in mineral soils.

Nitrogen fertilization in ecosystems that suffer from nitrogen deficiency is one possible way to affect the biomass growth. For example, in boreal forests nitrogen fertilization increased growth significantly and in fertilization treated plots stemwood production increased by 29-37% compared to non-treated plots (Mäkipää et al. 1998). Nitrogen affects the growth, which means accumulation of carbon in biomass, but it also has impact to soil carbon pools. Weather the impact is negative, positive or neutral, depends on several factors. For example, in boreal forests, soil organic matter accumulation is noticed

to increase by nitrogen input (because of increase litter input) (Mäkipää 1995). Other forest management practises are thinning, extending the harvest rotation and selection of species varieties (breeding) (Sedjo and Sohngen 2012).

4 Detecting the change in the biomass and soil carbon pools

Carbon accumulation or losses can be in general determined in two different ways: measuring pool changes and measuring incoming and outgoing fluxes (Houghton 2003). Estimations about different biomass and soil carbon pools are usually conducted with different methods (Fig. 5). Soil carbon pools can be quantified with direct soil sampling, sensing with spectroscopic methods or by modelling (Paustian et al. 2019). Biomass carbon pools can be quantified with inventory-based field measurements, remote sensing or modelling (Pearson et al. 2007). Incoming and outgoing fluxes can be used to measure the whole ecosystem (biomass and soil) carbon pool size (Smith et al. 2020).

Soil carbon stocks can be measured directly in units of carbon, but biomass is converted to units of carbon by multiplying biomass by 0.5 (IPCC default) or more specific values, if there is available data (Pearson et al. 2007).

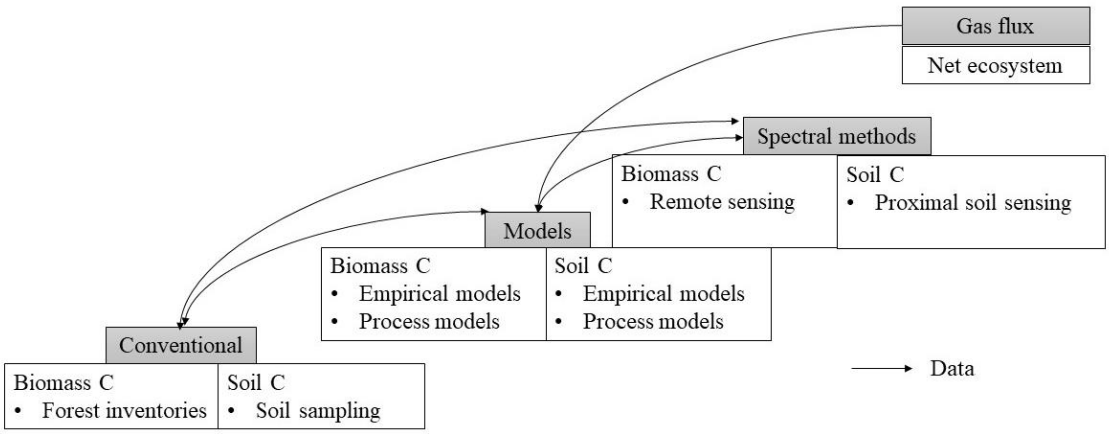

Fig. 5. Schematic picture of different carbon pool estimation methods and how they are linked together. Conventional soil and forest field samples provide information about current stock sizes and/or changes in those stocks. They also provided foundations to other methods. Spectral methods relay also to measured values, because there must be reference data to evaluate the reflectance. Modelling can be used to simulate carbon stock

sizes or changes in those stocks. They also link the remotely sensed data to the field measurements. Information from flux measurements and from remotely sensed data can be used to model development. Gas flux measurements present the net ecosystem carbon exchange (Pearson et al. 2007, Paustian et al. 2019, Smith et al. 2020).

Several European countries have launched networks to monitor the changes in soil condition (Morvan et al. 2008) and changes in biomass over time (Tomppo et al. 2010). But in European scale, the geographical distribution of monitoring networks is uneven, and in central and northern in Europe the number of sampling plots is higher than eastern Europe. Globally this same trend is recognized, and certain areas have representative study networks and some lack those completely. One large problem is also that networks differ considerably in their sampling protocols, designs, plot locations and sampling frequency. Sampling networks vary also within the country because some have different networks for different land-use types, like arable and forest lands (Heikkinen 2016, Tomppo et al. 2010). Long-term experiments are needed for data concerning processes that affect soil and biomass carbon and how different management practices affect the pools. These long-term field measurements also provide the basis for the calibration and validation of different models (Körschens 2005, Saarsalmi et al. 2012, Heikkinen 2016).

According to Pearson et al. (2007), to produce credible and transparent estimates of changes in carbon pools the following steps are needed: 1. A monitoring plan should include description of boundaries, project area, number of sample plots, project duration and monitoring frequency, 2. Information about the number of samples and other sampling protocols, 3. Carbon stock estimation methods and analyzing of the results. What are the actual methods and how they are utilized? What techniques are used for result analyzing? 4. Net change estimation. How the change in carbon stocks can be estimated? 5. A quality control plan. What is the accuracy in these estimations? Quality assurance (QA) and quality control (QC) for results (Fig. 6).

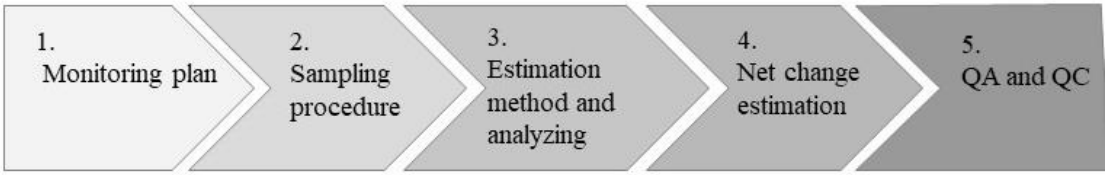

Fig. 6. Steps needed for estimation of changes in carbon pools.

According to Pearson et al. (2007), carbon stock estimations should be primary conducted with field measurements, because of their accuracy. Pearson et al. (2007) also suggested that precision target should be that with 95% confidence level, the true population value is ± 10% of the sample estimate. Because field measurements are not the most cost-effective way to monitor carbon stock changes, alternative methods could be used, if those reach robust precision enough. Good common practices for carbon accounting secure the reliable results. Good practices according to Watson (2009) are summarize in table (Table 1).

Table 1. Important factors that should be considered in carbon stock estimations.

Accurate and precise	Both accuracy and precision should be achieved. Biases and uncertainties should be removed as far as it possible.
Comparable	Assumptions, methods and data must be commonly accepted (scientific consensus) and should provide meaningful and valid results between areas.
Complete	All relevant carbon pools should be included. If some are excluded, it should be well justified and documented.
Consistent	Estimates from different quantifications should present the actual difference between pools. Differences should not emerge from differences in methods.
Relevance	Trade-offs between time, resources, data and methods should be appropriate to the purpose of the quantification.
Transparent	Results should be able to be confirmed by a third party.

All carbon stock and stock change estimation methods include sources of uncertainties or errors and there is no such method which would provide absolute true pool size value. It's important to identify the sources of errors and quantify their nature and magnitude. Estimations of these uncertainties are especially important if the results are used for policy purposes (Aubinet et al. 2012). For example, sustainable creditable carbon unit is a result of quantification method which full uncertainty is defined and considered. Resolution is also an important term. Resolution can be defined as the smallest change in the measured quantity that instrument can detect (Aubinet et al. 2012).

Precision, accuracy, and bias are commonly used terms when discussing about uncertainties related to measurements. Precision refers to the degree of agreement in a series of measurements and accuracy is the closeness of a measurement to the true value (Husch et al. 2003). Bias is a term that describes the difference between the true value of a target and its average measured value. Bias error can also be called systematic error. Systematic errors are consistent and repeatable errors. Random errors can be called for precision errors and those types lack repeatability. Scattered result in a repeated measurement is a common sign of random error (Husch et al. 2003). These two traditional error types propagate in different ways and thus it is important to differ those. Random errors are impossible to correct due to their random nature, and they typically cause noise and scatter in the data. Random errors reduce the precision of the measurements. Repeated measurements (increasing the *n*) is the only way to characterize the total random error. Averaging over *n* measurements improves the precision and result of this gives the standard error of the mean. Systematic error stays constant and it cannot be identified through statistical analysis (bias) (Aubinet et al. 2012).

Many carbon estimation methods rely on data-model fusion and different error types affect differently to the models. All models are as good as their most inaccurate parameter. Different error types at different stages affect the total uncertainty of the estimation. It's important to evaluate the magnitude of all possible errors (Lasslop et al. 2008).

5 Carbon markets

The Paris Agreement was launched 2015 and parties of the UNFCCC agreed to fight against climate change and to enhance investments needed for reach low carbon future. The Agreements central aim is to limit the temperature rise to 1.5 °C and thus prevent the harmful consequences of climate change. The Paris Agreement considers carbon sinks and reservoirs also as important factor as a tool for mitigating climate change, and The Agreement encourages Parties to enhance pools and to increase their sizes (United Nations 2020). European aims to be first carbon neutral continent in 2050 (European Commission 2020). To meet this target the EU is set several action plans, and for example European Green Deal is a package which includes first climate action initiatives, like

European Climate Law (European Commission 2020). European Climate Law is going to be a first law where EU aims to write the year 2050 climate neutral target. European Climate Law would ensure that all EU policies would make effort to reach that target. To reach that target all possible mitigation practices should be adopted and to enhance practices to increase natural-based carbon sequestration, political incentive should be launched (European Commission 2020). One possible way is international carbon markets and the Paris Agreement recognize the importance of this in Articla 6, where it's mentioned that carbon trading would help to achieve emission reduction targets. This kind of market mechanism would include that farmers and foresters could manage their land so that carbon sequestration is maximize and would achieve economic value from these practices by selling the creditable carbon units they have produce in the carbon pool. Creditable carbon unit is not yet defined, and there is no such regulated mechanism where transaction would be conducted (Ollikainen et al. 2020).

Climate change mitigation by changing the land management practises and at the same time providing excess income possibilities for farmers and foresters is a great goal to achieve. This approach would be a way to utilize the already existing, and possibly quite effective methods, but there are also several well-known issues associated to carbon sequestration projects via natural methods. Project issues usually contain the criteria which should be met so that it is possible to say that carbon is sequestrated from the atmosphere and it's now in adequately stable form and locates in stock. Baseline determination, additionality, possible carbon leakage and permanence (and non-permanence risk) are the most discussed issues (García-Oliva 2004, Sedjo and Sohngen 2012).

In carbon market framework, the baseline determination is the first thing to address. Credible and accurate baseline is needed for monitoring difference in carbon stocks. Baseline determination is also one of the most challenging issues. According to Carcia-Olivia (2004) two approaches have been used for developing and applying baselines. One approach is project specific. Baseline is established case-by-case. Other is generic, where baseline is determined by using regional or national data. Important component of assessing carbon sequestration is also to determine whether the carbon benefits of an activity are truly additional. Carbon benefits of certain project/action should be compared to carbon stocks between a with- and without- action scenario. Leakage can occur when

measurable carbon net change (decrease or increase) occurs outside wanted area due to project activity. For example, if farmer afforests land and after the afforestation of area deforests another land for agricultural purposes, the resulting carbon emissions are referred to as leakage. Monitoring and accounting leakage can be done either project specific or standardized. And because carbon sequestration is a reversibly process and carbon stored in terrestrial ecosystems are vulnerable to natural or anthropogenic disturbances the sequestrated carbon is not stored permanently. Fires and pests, harvesting and changes in land management and land-use may result to carbon release to the atmosphere (Carcia-Olivia 2004, Sedjo and Sohngen 2012).

Besides the tight criteria, there are also other challenges which should be resolved before well-functioning CO_2 emission markets. One big issue is high measuring/monitoring, reporting and verifying (MRV) costs of carbon sequestration. Current costs are high (see for example section 6.1.6) and MRV processes are complicated and they lack standards. Small-scale projects are important for the development of local carbon markets and MRV costs should be reduced in order to allow the progress. High MRV costs are identified as a challenge and some solutions are also presented. For example, group certification options, more diverse group of auditors to carry out verification and baseline and stock change estimation with less time-consuming methods would reduce the costs (Grimault et al. 2018, Köhl et al. 2020, Ollikainen et al. 2020). One approach is to value other benefits besides carbon to allow higher carbon prices. Well implemented carbon sequestration projects are usually multi beneficial, and environmental and social benefits could be added to carbon price value. Higher carbon value would increase the project profitability. This is a possible approach, but it also adds uncertainties in the achievement evaluation state (Sonwa et al. 2016, Köhl et al. 2020). It's hard and expensive to determine the size of the carbon stock change accurately and it would be even harder to evaluate the project impact for e.g. biodiversity.

6 Forest field measurements for biomass stock quantification

The conventional methods to estimate amount of biomass are harvesting to determine exact biomass and estimation approaches which rely sampling and statistics. Harvesting and directly measuring all biomass (weight and volume) is destructive method and it gives

accurate values (Husch et al. 2003). This type of approach is laborious and time consuming, but it provides basic data information to the different applications. For example, different allometric equations and growth models are conventionally used methods for biomass estimations and they are developed from information provided by destructive methods (Mäkelä and Valentine 2019). Destructive methods are part of the basic research and needed for better model development, model validation and to increase our knowledge of vegetation characteristics etc., but they are not suitable for biomass estimations in a purpose to estimate permanent carbon pools. Other forest field method, that don't include harvesting, is measuring diameter and height of trees and to identify different species and then link those measures to other three attributes like, total biomass, via allometry (Husch et al. 2003).

Husch et al. (2003) pointed out that the most economical approach to estimate aboveground forest biomass is to use data from forest inventories. National forest inventories are conducted in several countries and they have been common practice in many places for decades (Tomppo et al. 2010). On the other hand, several countries where carbon sequestration potential is high, forest inventories are not a common practice, which hampers the application. Small scale forest inventories are also conducted to research purposes (Tomppo et al. 2010).

6.1 National forest inventories

National forest inventories (NFI) are conducted to provide information about forest resources. Most basic variables that forest inventories produce are related to forest area and growing stock volume. Inventories are based on large field measurements, where tree parameters are measured. Field plot measurements and systematic or random sampling are ways to produce information which can be upscaled to comprehend large areas. In national forest inventories, the whole country is covered with regular networks of plot measurement clusters. These field measurements can be used for reliable forest statistics and calculations for larger areas (Tomppo 2014).

Information from forest inventories are usually used for example policy making, forest management planning, assessing sustainable forestry, greenhouse gas and carbon stock evaluation and research (Tomppo 2014). The first NFI in Finland was carried out in

1921−1924 (Tomppo et al. 2010). Current day inventory in Finland is multisource inventory where several data sources are utilized (field measurements, satellite data and digital maps) (Tomppo 2014). Most European countries conduct forest inventories, for example Austria (first 1952−1956), Sweden (first 1923−1929), Spain (first 1965−1974), Great Britain (first started 1924) and Italy (first 1986−1988). USA (first started 1928) and Brazil (first 1980s) are also managing their forest resources through inventories. Canada is one of the biggest forest countries, where national forest inventory is not mandated through legislation. China (first 1973−1976), Japan (first started 1951), The Republic of Korea (first 1960s), New Zealand (first 1946−1955) and Russian Federation (first 2007) are counties in Asian continent that conduct inventories (Tomppo et al. 2010).

6.2 Allometric equations

Allometric equations are mathematical models that describe the relationship between tree characteristics that are easier to measure to another tree properties that are hard to measure. This relationship is typically based on detailed measurements of vegetation, where small sample size is representing a population of interest (Mäkelä and Valentine 2019). Easier tree determinations are for example diameter and total tree height and harder ones are volume or biomass. Diameter is typically measured from chest height and the total height can be estimated with a hypsometer and leveling rod. For example, biomass equations are developed from harvested and weighted vegetation samples. Each sample is oven dried, weighted with high detail, stem, stump, roots, branches and foliage separately, and after sufficient number of samples, some consistency can be seen. With regression techniques, certain parameters of allometric equation that relate biomass and measured variables can be found (Moore et al. 2010, Birdsey et al. 2013). Each allometric equation is as good as its parameters are (Mäkelä and Valentine 2019). Individual tree estimates can be expanded to larger areas by knowing the probability of sampling each tree (Birdsey et al. 2013).

Different biomass or volume equations are a cost-effective way to evaluate large areas, but there is scarcity of representative equations. Population of trees under interest maybe different than population from where the equation was developed, and if only few equations are available, there is a problem. This issue is particularly true in tropical regions (Rex et al. 2020). Generalized biomass equations can be used when local or

species-specific biomass equations are not available (Birdsey et al. 2013). Biomass equations are typically presented to individual species, groups of species (Zianis et al. 2005, Pearson et al. 2007) or for geographic regions (Duncanson et al. 2015). Allometric equation are also typically developed to forest trees which diameter at breast height (DBH) is bigger than 10 cm and equations for smaller trees are rarely available. This means that forest understory vegetation is difficult to estimate cost-effectively (Han and Park 2020).

One example of allometric equation which can be used to calculate oven-dry tree biomass M (kg) according to Brown (1997) is shown in equation 1.

$$M = a + bDBH + cDBH^2 \quad (1)$$

in which
DBH = diameter (cm) at breast height (1.3m)
a,b,c = best fit parameters.

Biomass growth can be also simulated with growth models. Growth models combine carbon allocation models to factors affecting carbon accumulation (Mäkelä and Valentine 2019).

6.3 Estimating carbon stock from forest inventories

Most forest inventories are focused on timber estimation, but constant need for information about forest health, soils, wildlife and other nontimber values have created development of integrated or multisource inventories (Husch et al. 2003, Tomppo 2014). Information from a timber inventory is insufficient for a complete estimate of a carbon stock, because they usually estimate only the volume of the main stems, ignoring other components of the vegetation and other carbon pools in the ecosystem (Husch et al. 2003, Lindner and Karjalainen 2007, Tomppo 2014). Carbon stock estimations need an inventory of the total biomass of live standing timber, biomass of the understory vegetation and estimations of dead biomass, root biomass and soil carbon pools. Total biomass can be adjusted with an expansion factor to include all other biomass quantities

(Husch et al. 2003, Lindner and Karjalainen 2007) or other carbon pools could be also estimated by conducting additional measurements at the inventory (Birdsey et al. 2013). If inventories are conducted so that other biomass is ignored, to include weights of these components (roots, foliage, understory vegetation and detritus on the forest floor) the weight of the commercial volume should be multiplied by an expansion factor which typically varies from 1.3 to 2.5 depending on species, forest age, average tree height and amount of dead matter. Expansion factors are generated from allometric relations (Husch et al. 2003).

Carbon pools locates in vegetation biomass aboveground and belowground, and each pool needs different sampling methods (Pearson et al. 2007). Size of those carbon pools vary, and it should be decided if the certain pool is cost effective to estimate for certain purposes. Live trees and their roots are important to include to all activities. Understory vegetation and nontree biomass maybe be beneficial to measure and monitor only if they are significant component of the total biomass (Lindner and Karjalainen 2007, Pearson et al. 2007). This is the case in areas where the main biomass consists mainly from shrubs and other form of nontree vegetation. Some forests may mainly composite from big trees and understory vegetation is not a large part of total biomass. The forest floor should be included in carbon pool accounting in most cases, especially in conifer dominated forest, because it is known that in this type of forest the biomass in forest floor consists big part of the total pool. Understory vegetation in the forest inventories can be measured with harvesting technique, where small subplots are harvested, and vegetation is oven dried, pooled to composite sample and weighted. After measuring, the information can then be upscaled to the whole plot (Lindner and Karjalainen 2007, Pearson et al. 2007).

Amount of biomass can be calculated with equation (2) and multiplying by 0.5 the metric t/ha for the amount of carbon (Pearson et al. 2007).

$$\textit{Oven-dry weight (g) of biomass / sampling frame area (cm}^2\textit{) * 100} \quad (2)$$

in which
multiplying by 100 converts the unit to metric t/ha.

Below-ground biomass comprehends coarse and fine roots and they are included to carbon pool accounting by applying a regression models which links belowground biomass to aboveground biomass. Example Cairns et al. (1997) developed regression models that can be used in different forest biomes (equations 3−5):

$$Boreal: BGB = \exp(-1.0587 + 0.8836 * lnAGB + 0.1874) \quad (3)$$

$$Temperate: BGB = \exp(-1.0587 + 0.8836 * lnAGB + 0.2840) \quad (4)$$

$$Tropical: BGB = \exp(-1.0587 + 0.8836 * lnAGB) \quad (5)$$

in which
BGB =belowground biomass density in t/ha
AGB= aboveground biomass density t/ha
(n=151; R^2=0.84.).

Dead biomass comprehends dead organic matter in forest floor and dead trees (on the ground or standing). Forest floor dead biomass should be estimated like living forest floor biomass (Pearson et al. 2007). Most time-efficient way to estimate carbon stocks in dead wood is the line intersect method, where each dead wood intersecting at least 100 m length (per plot) line is measured and classified via density (Harmon and Sexton 1996). There are different density classes and they are developed by forest scientists and they are based on different decomposition models of dead wood (Beets et al. 1999).

Most accurate and precise carbon stock estimation of trees is achieved with direct methods where all trees (above a minimum diameter) in sample plot are measured (Lindner and Karjalainen 2007, Pearson et al. 2007). The minimum diameter varies according to trees that are expected to be found in a sampling area. Environments where the trees grow slower (e.g. arid) the minimum diameter may be 2.5 cm and in humid environments, where the tree growth is fast, the value may be up to 10 cm (Pearson et al. 2007). Tree biomass is often estimated with equation where only the diameter at chest height is used as a variable. Height and diameter as the independent variables result better estimates but measuring the tree height increases the cost of monitoring. If there is vast monitoring network with plenty of data, the regression equation with diameter only can result a high significance (Lindner and Karjalainen 2007, Pearson et al. 2007), but if not the variation of total biomass estimations could be high. For example, the total estimate

of tropical forest carbon biomass stock varies by 35.3 Pg depending if the height is included (Feldpausch et al. 2012).

6.4 Inventory planning and sample size

Available funds and the costs of an inventory will influence the chosen design (Husch 2003). Main factors affecting the costs are precision, total size of the area and the minimum size of the unit area where estimates are required. The accuracy requirement defines the number on needed sample plots. Keller at al. (2001) calculated the required number of plots and total sampling area for biomass estimations if total error is within 20% of mean with 95% confidence (table 2). When the area increases the total number of required samples decreases.

Table 2. Required number of sample plots and total area to meet error less than 20% (Keller et al. 2001).

Plot size (ha)	n	Total area (ha)
0.09	43	3.87
0.25	21	5.25
0.49	15	7.35
1.00	10	10.00
1.96	8	15.68
4.00	6	24.00

6.5 Uncertainties in forest inventories

According to Husch (2003) typical errors sources in forest inventories are sampling error, measurement error and prediction error from used models. Classification error of remote sensing imagery is also one error source, if remote sensing is used. The essential problem in inventory-based approach is that obtained samples should represent the population. If samplings are representative, useful statements can be made about characteristics of the population, like volume or weight per unit area, number of trees etc. These characteristics, parameters, exact values would be known if the entire population would be measured, but due the time and cost factors, sampling provides estimated values for these parameters. Estimates are calculated from samples and these statistics are summary values which represent the whole population. If determined parameters are not representative it will

lead to a sampling error. That's why the efficient sampling design is important. The used sampling units, the number of samplings, the manner of selecting and distributing the sampling points over forest area, measurement and result analyzing procedures are all important parts trying to decrease the sampling error (Lindner and Karjalainen 2007, Husch 2003, Tomppo 2014).

Keller et al. (2001) calculated the size of the sampling error and other error sources (table 3) in the Amazon area field measurements and data analysis. Their results show that in mean sampling error was approximately 15%. Field plot aboveground estimation's uncertainties has been reported to be even 20-30% (Keller et al. 2001, Chave et al. 2004).

Table 3. Biomass density estimations with related errors.

	Mass (Mg/ha)	**Sampling 95% CI (Mg/ha)**	**Other error (%)**
Trees (DBH≥35cm)	177	24	20
Trees (15<DBH<35cm)	47	10	50
Trees (DBH<15cm)	40	8	50
Vines and epiphytes	18	2	50
Dead fine AGB	8	2	50
Dead coarse AGB	19	3	50
All below-ground	63	9	50
Total biomass	372	56 (15%)	

Measuring tree height is time consuming and it's possible that height is not measured form all trees form inventory plots (Sullivan et al. 2018). For example, The Amazon Forest Inventory Network RAINFOR, the guideline is to measure the height of 40 trees in 1 ha area if time prevents all trees being measured (Phillips et al. 2009) which means that in tropical forests 90% of tree heights are not measured but predicted. Different prediction models perform differently, and the performance can be estimated by calculating prediction error. For example, root mean square error (RMSE) can be used to describe the difference between measured and predicted heights (Sullivan et al. 2018).

Measurement errors include errors that arise from defects in the sampling procedure, like mistakes in data collection or processing. Measurement errors don't decrease when increasing the sample size. For example, appropriate training of field crew, quality

control, appropriate mathematical models and well-prepared maps would reduce the nonsampling errors (Husch 2003).

6.6 Accuracy and cost of forest measurements

In-situ sampling costs depend on design, the number of attributes to be collected, salary levels and on the accessibility of the forest area. Costs increase with accuracy. Berenguer et al. (2015) studied how forest carbon stock could be quantified through field measurements in cost-effective way. They conducted the study in Amazon, which is area lacking intensive field measurements. Several tropical countries are suffering this lack of filed measurement. Study site included 224 sampling plots spread evenly to two 5000 ha areas (three different forest type). They conducted field measurements to all biomass carbon stocks and soil. These results were compared to simulations where single value for wood density was used, without identifying the stems. They also compared the field measurements to default values, defined by FAO and IPCC. The total cost quantifying carbon stocks of field sampling by assessing each forest component was 364 000 US$ (~311 000 €) with 224 0.25 ha forest plots. They calculated that without species identification the costs would decrease by 58%. This reduction would be due to decrease in salary costs when experienced taxonomic experts are not needed. They also noticed that forest soil was by far the most expensive and time-consuming part to measure (with conventional soil samples and dry combustion method). In their study, the soil sampling cost approximately 2250 US$ (~2680 €)/ha and identification and measuring large and small stems cost ~500 US$ (~595 €)/ha each.

Berenguer et al. (2015) also expressed the average error compared to intensive field measurements with unit Mg C/ha. Field sampling with species identification gave errors close to zero (accurate values were not presented in article). Protocol where stems were measured but not identified gave average errors of 2.69 Mg C/ha, 6.42 Mg C/ha and 14.22 Mg C/ha which represent 3%, 5% and 31% of the total carbon stocks contained in those stems (average from different areas, three different forest types). FAO default values gave average errors of 21.16 Mg C/ha and 5.02 Mg C/ha (value for two different areas, forest type doesn't matter in default values). IPCC values performed poorly, average errors were 50.16 Mg C/ha and 34.02 Mg C/ha.

7 Remote sensing of aboveground biomass

Remote sensing is a method where different sensors are used from distance, for example, from airplanes or satellites (French 2013, Angelopoulou et al. 2019). Remote sensing is used for large scale biomass estimations (aboveground carbon stocks), and although other spectral methods are typically used for below ground carbon estimations, remote sensing is not yet robust method enough for that. Remote sensing of soil organic carbon is also limited to few first centimeters of bare topsoil (Vaudor et al. 2013, Angelopoulou et al. 2019).

Remote sensing procedures have been applied to collect information about aboveground biomass. Vegetation structure, biomass and productivity can be estimated on a large scale by measuring the spectral reflectance of the vegetation (Main-Knorn et al. 2011, Vicharnakorn et al. 2014). According to Canada Centre for remote sensing (2020), remote sensing refers to a science where information concerning the earth's surface is collected by sensing and recording emitted or reflected energy. Processing, analyzing and applying that information is part of that science. Remote sensing can be conducted from space (satellite systems) or air (airplane, drone). Aerial sensing is used for local-scale assessment of earth surface and satellite systems can be used for larger spatial extents (French 2013). Remote sensing needs some field measurements, the ground truthing, that is the way to link the sensor data to biophysical phenomena (French 2013).

Aboveground biomass estimations are usually conducted with optical, Radar (SAR) and light detection and ranging (Lidar) sensors (Issa et al. 2020). Aboveground biomass is not spatially mapped even in countries where systematic forest inventories are conducted (French 2013). Mapping would add important information about carbon stocks, because forest characteristics can differ greatly from inventoried ones. Some areas are not easily accessible and remote sensing would be good opportunity for those (Vicharnakorn et al. 2014, Holopainen 2019). On a national scale, above ground carbon stocks can be overestimated or underestimated if only field approach is used (French 2013).

7.1 Basics of remote sensing of biomass

According to Canada Centre for Remote Sensing (2020) remote sensing needs an energy source that illuminates or provides electromagnetic energy. This energy travels towards its target of interest and while travelling comes into contact with atmosphere. Interaction with atmosphere takes place a second time as the energy travels from the target to the sensor. After the energy makes it way to the target, they interact with each other depending on the properties of both. After the interaction, the next step is to record and collect the electromagnetic radiation. This can be done via a sensor, which is not in contact with the target, that collects the scattered or emitted energy from the target. Then the energy recorded by the sensor must be transmitted to the station where the data is processed into an image. Lastly processed images can be interpreted visually, digitally or electronically, so that information about the target, which was illuminated, can be extracted (Canada Centre for Remote Sensing 2020). All electromagnetic radiation behaves in predictable ways in accordance to the basics of the wave theory (Canada Centre for Remote Sensing 2020).

The interaction between a sensor and the surface can be active or passive. Passive sensors measure naturally available energy. These kinds of remote sensing systems can be used when the sun is illuminating the Earth (reflected energy), and during day and night when naturally emitted energy is available (for example thermal infrared) (Canada Centre for Remote Sensing 2020). Passive sensors usually record electromagnetic waves from visible (430−720 nm) and near-infrared (750−950 nm) range of light (Zhu et al. 2018). Active sensors provide their own energy source which means that the sensor emits radiation and detects and measures the radiation reflected from the target. These kinds of systems work regardless of the time of day or season (Canada Centre for Remote Sensing 2020). Active sensors use electromagnetic waves in the range of visible light, near infrared and radio (Zhu et al. 2018). Wavelength of the electromagnetic radiation and the characteristics of target affect the reflectance spectra. Each target has its own spectral signature and this information can be utilized in remote sensing. Spectral signature is affected also by e.g. season, time of the day and position of the radiation, which all affect the interpretation of the images (Campbell et al. 2008).

Remote sensing for biomass carbon stock estimation is challenging but offers a broader scale estimation when compared to field observations (Gibbs et al. 2007). Remote sensing for carbon estimations can be separated into two main methodologies (Iizuka and Tateishi 2015). The first is the indirect measurement of carbon (physical method) and the second is a method where land cover information is integrated with observations of forest inventories (statistical method) (Goetz et al. 1999, Pachavo and Murwira 2014). In the indirect approach gross primary production (GPP) or net primary production (NPP) is estimated with several parameters that are related to vegetation functions. Such parameters include leaf area index (LAI) and photosynthetically active radiation (PAR). In the statistical method, the field reference measurements and remotely sensed picture characteristics (e.g. pixel shade) are linked with regression techniques (Holopainen 2019). Both methods can also be integrated together (Zheng et al. 2007). Remote sensing can be conducted on a regional to global scale depending on the resolution of sensors and purpose of the use (Angelopoulou et al. 2019).

7.2 Resolutions of remote sensing instruments

Different remote sensing instruments have different resolutions (table 4). Spatial resolutions refer to the smallest object, pixel, that sensor is capable to detect. Spatial resolution determines how detailed a picture can be. Temporal resolution tells how often satellite passes the same spot and spectral resolution refer to sensors ability to sense different wavelengths. In spatial and temporal resolution, high resolution refers to small number of units (for example days or meters), and opposite in spectral resolution, where high resolution means that sensor can sense several wavelengths. There is usually a trade-off between spatial and temporal resolution, which means that high spatial resolution pictures can be taken less frequently (Ympäristöministeriö 2004).

Table 4. Satellite remote sensing resolutions (example, values vary slightly between sources) (Ympäristöministeriö 2004).

	Resolution		
	Spatial	**Temporal**	**Spectral**
High	1-35 m	< 3 days	several hundred bands
Medium	200−500 m	4−16 days	3−15 bands
Low	> 1000 m	> 16 days	3 bands

For large (global and continental) scale biomass mapping the coarse spatial resolution (>100 m) optical sensors, such as the MODIS (French 2013), are useful because they have moderate spatial resolution, and good image coverage and frequency in data acquisition (good trade-off between those). Smaller (local to regional) scale biomass mapping needs finer spatial resolution instruments to achieve data with more details (Lu 2007).

According to Lu (2007), vegetation estimations with coarse spatial resolution data over larger areas have been limited by the errors caused by mixed pixels, and the major difference between the pixel size of the satellite and the ground reference data. Mixed pixels case a situation where the coarse resolution pixels receive response from several objects (such as trees), and from that data, biomass cannot be directly estimated. Because coarse imaging satellites have useful characteristics (e.g. good image coverage), finer spatial resolution satellite data has been used to combine ground reference data to this coarser spatial resolution data. This is usually done by regression techniques (Muukkonen and Heiskanen 2007). For example, Häme et al. (1997) derived regression models from ground reference data and Landsat satellite data which they utilised successfully in the medium coarse spatial satellite data. Finer spatial satellite data models can be used as an intermediate step between ground measurements and coarse resolution data.

7.3 Different sensor approaches for biomass estimations

Three main sensor approaches are used for vegetation carbon storage estimations: optical sensors, synthetic aperture radar (SAR) and Lidar (Sun and Liu 2019) (Table 7). Optical sensors and their spectral measurements have been used to model and monitor primary production of above ground vegetation (Song 2012, French 2013). Optical imaging

sensors operate in the visible and reflective infrared ranges. Aerial photographing was the earliest version of remotely sensed data and it has been used to local-scale assessments (French 2013). Larger spatial scale remote sensing with satellite platforms and optical systems have been used for several decades (French 2013). Optical instruments on space platforms typically include panchromatic systems, multispectral systems and hyperspectral systems (Zhu et al. 2018).

Landsat is one of the optical satellite systems which can be utilized for carbon mapping. Landsat land observation was launched in July 1972 and it has been orbiting earth since then (French 2013). Landsat is high spatial resolution satellite (30 m resolution) and its collected data is publicly open. There are also commercial high spatial resolution satellites, like QuickBird (measuring visible to infrared region). Landsat and QuickBird are passive optical sensor systems. Landsat collects data at specific multiple spectral wavelengths (optical multispectral remote sensing), measuring visible spectrum. Optical instruments can also collect data across the entire spectrum of reflected solar energy (optical hyperspectral remote sensing). For example, NASAs operating airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor is hyperspectral sensing system (Hbirkou et al. 2012, French 2013). Satellite optical imaging system's spatial resolution varies from under 1m to 2 m (high spatial resolution) (Zhu et al. 2018). Variation depends from the sensor (e.g. QuickBird under 2 m, MODIS 250m) (Zolkos et al. 2012).

Optical remote sensing does not directly asses the aboveground biomass (Vicharnakorn et al. 2014), but it gives two-dimensional information, which can be linked to biophysical characteristics of the vegetation. This linkage is indirect and optical systems can be used to identify horizontal variability and, for example, to asses canopy conditions (French 2013). The electromagnetic energy that optical sensors utilize is emitted or absorbed on the upper layers of vegetation, so it only gives limited information (does not penetrate through vegetation) (Zolkos et al. 2012). This remote sensing system has been widely used to link direct aboveground measurements to satellite observations due to fact that different canopy structure gives different reflectance. This method is not consistent over large areas because rapidly varying surface conditions cause artefacts to the derived maps, as the satellite observations cannot keep up (cloud free time, repeat time). Frequent repeat measurement sensors, like the Moderate Resolution Imaging Sensor (MODIS), have

helped to overcome this problem (Goetz et al. 2009). Optical remote sensing systems are sensitive to optical properties and moisture (Zolkos et al. 2012).

Synthetic aperture radar (SAR) produces images based on principles of radio detection and ranging (RADAR often synonym for SAR) (Goetz et al. 2009). SAR is active system and uses microwaves, an electromagnetic spectrum range of 1 mm−1 m (Zhu et al. 2018). SAR can penetrate through haze, smoke and clouds, and it can operate during day and night. SAR transmits microwave energy which can penetrate forest canopies. SAR sensors are sensitive to different aboveground biomass components according to the wavelength of the sensor. Shorter wavelengths are more sensitive to leaves and small branches, and longer wavelengths are more sensitive to stems and large branches (Goetz et al. 2009). SAR only shows the geometry and surface roughness of the target and it does not produce data where you can identify for example the vegetation type (like infrared, and they are used to complement each other's) (Zhu et al. 2018). Several radar satellites are currently operating, for example the European ENVISAT/ASAR, the Japanese ALOS/PALSAR and German TerraSAR-X (Goetz et al. 2009).

One of SAR system's disadvantages is that its estimations of AGB are limited as the SAR instruments lose their sensitivity with increasing biomass (Issa et al. 2020). This phenomenon is known as "saturation" and it occurs in relatively low, but undetermined, biomass densities (optical saturation point is around 100−150 Mg/ha and for SAR a bit higher) (Zolkos et al. 2013). Low saturation point causes uncertainties in AGB mapping because estimations of vegetation density in high density forest is not accurate. Current SAR systems can produce an image with a half meter of accuracy (Zhu et al. 2018). It measures forest structure with high spatial resolution (20−100 m), can operate regardless of the time of the day and it can penetrate through clouds and through vegetation (Zolkos et al. 2013).

Lidar uses a pulse of energy from a laser operating at optical wavelengths to actively sense vegetation. Lidar systems that are typically used for vegetation mapping usually operate in wavelengths between 900 and 1064 nm. They record the time the pulse is travelling, and that time-return interval can be used to calculate distance between the sensor and the object (Zolkos et al. 2013). Lidar's laser beam width varies (small to large footprint) and a small footprint beam typically illuminates a surface area with a diameter

50 cm or less. This kind of accuracy provides information that is increasingly utilized in forestry applications but in a small area. Medium to large footprint lidars illumination surface area can vary from larger than 5 m to approximately 65 m (depending the platform) (Zolkos et al. 2013). A lidar can measure the three-dimensional vertical structure of vegetation in great detail (Vierling et al. 2008). This information can be applied to above ground biomass via correlative models which has been derived from associated field measurements (Zolkos et al. 2013). There are some lidar's operating form satellite platforms. The geoscience Laser Altimeter System (GLAS) spaceborne lidar system which be used to estimate forest aboveground biomass on a large scale (Sun et al. 2019).

Airborne Lidar is scalable and cost effective (Asner et al. 2013). Lidar and biomass have reported to show strong relationship beyond biomass levels of 1000 Mg/ha, which is far more than SAR and Optical sensors are capable. Lidar can estimate the vegetation structure direct (e.g. canopy height distribution) and it has been shown in several studies that it provides more accurate results in AGB estimations than optical and SAR data. Lidar can't penetrate clouds (Zolkos et al. 2013).

7.4 Important issues influencing biomass estimations for carbon mapping

Remote sensing for aboveground biomass estimations include several critical steps to consider when building a proper biomass estimation procedure (Fig. 7). The selection of the sensor and platform, sample size of the reference data, variables, algorithms and cross validation of data is important, and each step include uncertainties (Sun et al. 2019). Many studies have conducted aboveground estimations, but comparing those studies is difficult due to diversity of data sources, modelling methods and calculation standards (Sun et al. 2019).

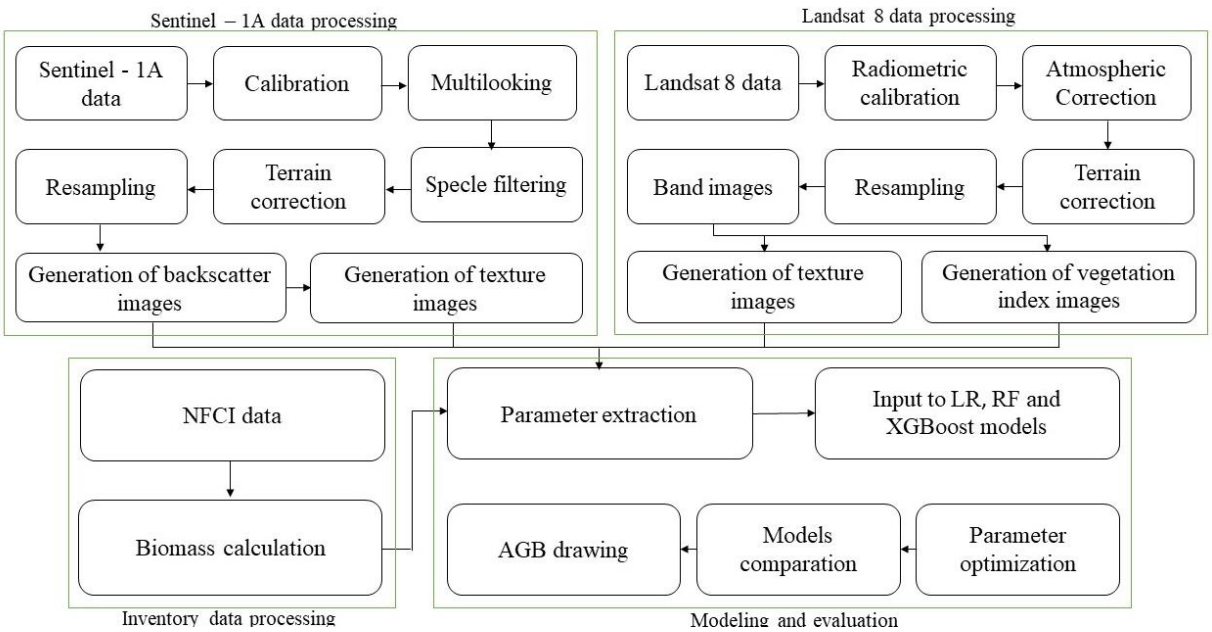

Figure 7. Workflow of satellite image processing. Combination of Sentinel and Landsat data (closely adopted from Li et al. 2020).

Assessing carbon stocks with remotely sensed data uncertainties are high. Each workflow step includes possible error sources and ecological subjects are hard to monitor with high accuracy. This means that vegetation structural variations, species composition, heterogeneity of landscapes, soil properties, climatic and topographic variables and disproportionate data availability all create high uncertainties that affect biomass division and change tendency (Issa et al. 2020).

7.4.1 Remotely sensed data

Remotely sensed data introduces limitations and sources of uncertainties. Different sensing systems provide different information and the selection of the right sensor data is essential. For example, each sensor type provides different resolutions and different information according to the polarization and angularity (Lu 2007). Sensor selection according to a specific purpose and study area is the key, and since each sensor type has their own characteristics, they can be integrated to achieve data where one sensor's limitations are exceeded. Multisensor synergy can produce estimations with accuracy levels similar to those of the lidar alone, or even better accuracy, but study results have varied (Zolkos et al. 2013).

Remotely sensed data needs also several corrections due to the radiometric characteristics and interaction with the atmosphere (Lu 2007). When electromagnetic energy passes through the atmosphere it causes changes to direction, intensity and spectrum of the radiation. These atmospheric effects need to be corrected, and typically it is done via mathematical models. Without proper atmosphere corrections, satellite pictures will show major distortions (Muukkonen and Heiskanen 2007). Atmospheric correction with mathematic models is necessary, but they also include inaccuracies (Muukkonen and Heiskanen 2007). Topographic factors also influence the reflectance of the vegetation and remotely sensed data from mountainous regions needs removal of topographic effects (Lu 2007). It goes without saying that remotely sensed data handling requires a thorough knowledge of data processing and an understanding of the phenomena under interest.

7.4.2 Reference data quality and variables

Remote sensing data is conventionally compared with forest *in situ* measurements (non-destructive estimations) (Zolkos et al. 2013). Forest field measurements are essential for biomass estimations and field measurements can also be called reference data. The field measured data can be used for different purposes e.g. model development, validation, calibration, comparing different models and to conduct uncertainty analysis. High quality data source is thus essential for developing an AGB estimation model. The quality of the field data may vary greatly because data is essentially collected for another purposes, tree species composition might be very complex and wood density may differ (Lu 2007). Quality of field data affects the accuracy, and calibration or validation of the calculated AGB is needed. Asner et al. (2013) argued that to reduce uncertainties in lidar and satellite measurements, the necessary step is to measure plot-level biomass instead of estimating it from conventional inventories with allometric equations. More accurate plot level direct measurements offer better data for lidar calibrations.

Geometric accuracy of the field data sample plots and remotely sensed data is also important factor affecting the accuracy of the biomass estimations (Lu 2007). Without proper geometric accuracy, the relationship between AGB and remotely sensed data can be erroneous.

According to Issa et al (2020) one factor affecting biomass estimations is selection of suitable remote sensing variables. Remote sensing variables, such as spectral signature, vegetation indices and image textures, may be suitable parameters to describe AGB. Suitable variables should correlate significantly with AGB and weakly with each other's. Weak correlation with AGB reduces the AGB estimation performance. Potential parameters can be identified with several statistical methods. For example, stepwise regression analysis and correlation analysis can be used. Both are simple analysis which are based to the relationship between AGB and tested variables (Issa et al. 2020).

7.4.3 Modelling and uncertainty analysis

Different modelling algorithms can be used to describe what remotely sensed data tells about phenomena of interest, which is in this case aboveground biomass (carbon pool). Algorithms link reference data to the variables divided from remotely sensed images (Gasparri et al. 2010, Dormann et al. 2012). Empirical algorithms include parametric and nonparametric algorithms, and both are widely used in aboveground biomass estimations (Sun et al. 2019). Parametric algorithms (e.g. simple or multiple linear regression model) and nonparametric algorithms (e.g. K-nearest neighbors, random forest) behave a bit differently. Parametric algorithms assume straight forward linkages between variables and biomass and estimation are based on models which predict the relationship (Powell et al. 2010). But in real life, factors affecting biomass are complex and numerous, which means that it is difficult to predict the relationship with simple regression models. An alternative approach is to use nonparametric algorithms (Sun et al. 2019).

Several factors determine which model/algorithm/prediction method is selected (Sun et al. 2019). Factors, such as, sensors resolution, the availability of biomass sample data and reference data, the scale of the area, the availability of related software and human resources all affect the selection of prediction model. Different models perform differently according to factors mentioned above. One way to evaluate model performance is uncertainty analysis. Uncertainty analysis is used to assess the accuracy of biomass estimates. The root mean square error (RMSE) and the coefficient of determination (R^2) are commonly used measures (Lu 2007). High R^2 value and low RMSE value often indicates that developed model fits well with the sample plot data. Traditionally, in remote sensing data analysis, the reference data is split into two parts,

where one part is used to develop the model, and other is used for evaluation of model performance (cross-validation) (Sun et al. 2019). Uncertainty analysis is one way to compare performance of different approaches but there is also variation between analyzed results. For example, one of the common types of cross-validation method is k-fold cross-validation, but the value of k differs in different studies and that might affect the model diagnostics (Sun et al. 2019).

Sun et al. (2019) studied the performance of different prediction methods by combining lidar data (GLAS), optical data (MODIS) and field measurements. They compared six prediction methods (Gaussian processes, stepwise linear regression, nonlinear regression, partial least squares regression, random forest and support vector machines) and effect of prediction method, sample size of field measurements and cross-validation settings. Authors concluded that prediction method had the most considerable effect on the quality of the estimations. In most cases the random forest -model produced more accurate predictions than others. The sample size obviously affected the prediction model performance and for example the random forest algorithm combined to large number of field measurements (n=801) gave the most precise results (R^2=0.73 and RMSE=23.58 Mg/ha).

Several approaches have been developed, yet there is no universal model, or at least agreement which model would perform best in certain situations. One universal model might be too difficult to develop, but it is necessary to identify (or develop) models suitable for different environments. More advanced models for AGB estimations, which utilize multi-source data, are also needed (Lu 2007).

Asner et al. (2013) demonstrated the uncertainty of aboveground carbon density estimations by combination of lidar sensors and satellite (Landsat) data. Accuracy was compared to field measurements. Study was conducted in Panama, and study site was the whole country. Vegetation types ranked from dense tropical forest to grasslands. The result demonstrated that the lidar based carbon mapping has an uncertainty of about 10% at 1 ha resolution.

Fassnacht et al. (2014) compared how sample size, sensor type and prediction method affect the accuracy of the AGB estimations. They conducted the study in two locations,

in Europe and South- America, and they compared three different sensor scenarios and they performance with different sample sizes and different prediction methods. Authors concluded that selection of sensor type had the highest impact on accuracy. In their study, the best performing sensor scenario was a combination of airborne lidar data and spaceborne optical data (compared to airborne optical and airborne lidar). Best performing prediction method was again random forest. The overall best performance was multisensory synergy with random forest algorithm and biggest sample size (R^2 0.71 and RMSE 37, case mean was R^2 0.42 and RMSE 52). The main discovery in their study was that a good prediction method might be more important than increasing the number of the field data.

7.5 Accuracy of remote sensing methods for biomass estimation

Accuracy requirements for remote sensing approaches are not yet explicitly stated, but studies conducted by Hall et al. (2011) and Houghton et al. (2009) asserted that satellite remote sensing should give errors in biomass estimation within 20 Mg/ha or 20% of field estimates. Errors should not exceed 50 Mg/ha for a global biomass map at 1 ha resolution (Zolkos et al. 2013). Asner et al. (2013) concluded that fraction cover of photosynthetic and non-photosynthetic vegetation imagery from Landsat, combined to topography and climate data, is a suitable way to map national-scale aboveground vegetation density on a per hectare basis. This method gives low uncertainties to estimations. In Panama study, Asner et al. (2013) calculated that carbon density uncertainty was on average 20.5 Mg C/ha at the national level.

7.6 Costs of remote sensing

Economic condition is probably the most important factor affecting the implementation of satellite remote sensing for carbon mapping (Issa et al. 2020). Economic condition influences the extent of the field work, purchase of different sources of image data and the human resources that all affect the accuracy of the AGB mapping. Higher accuracy often means higher costs. Asner et al. (2013) estimated that their costs for airborne lidar inventory was 1 USD dollar (0.85 €) per hectare in an area of 600 000 hectares. Costs of airborne lidar approach decrease when area increases and Asner et al. (2013) estimated

that for example cost for twice as large area, the cost per hectare (airborne lidar acquisition and analysis) would be about 0.15 USD dollars (0.13 €).

Böttcher et al. (2009) collected costs for monitoring Reduced Emissions from Deforestation and Degradation (REDD) projects in different areas and different project scales (table 5). They concluded that cost can vary from 0.42 to 463 €/km^2. These project areas were smaller (40−28000km^2) than area in Asner et al. (2013) study, but results differ from each other largely.

Table 5. Biomass monitoring costs with different remote sensing techniques (acquisition and analysis costs) example.

Satellite, sensor	**US$/km^2 (€/km^2)**
Optical, medium	0.50−1.21 (0.42−1.02)
Optical, high	7.50−35.40 (6.32−29.83)
Optical, very high	116−272 (97.74−229.18)
Radar, satellite SAR	7.04−10.54 (5.93−8.88)
Radar, airborne SAR	>345 (290.68)
Lidar, airborne	100−550 (84.26−463.41)

7.7 Summary of different aboveground biomass remote sensing sensors

Short summary of different biomass remote sensing approaches for carbon estimation (Table 6).

Table 6. Summarization of average R^2 values, average prediction errors, limitations and benefits of different remote sensing sensors for aboveground biomass estimations in forest (modified from Issa et al. 2020).

Sensor type	Spatial resolution/approach	Average R^2 and average predictive error	Limitations	Benefits
Optical	Coarse >100 m (e.g. MODIS)	R^2 value 0.58 and predictive error of 42%	Saturation at high biomass density Mismatch between the size of field plots, field measurements and pixel size Can't penetrate clouds Can't separate vegetation structure	Availability AGB mapping for continental and global scale High temporal frequency Consistent spatial data
	Medium 10-100 m (e.g. Landsat, SPOT)	R^2 value 0.68 and predictive error of 32%	Single pixel can include many tree crown or noncrown features Can't penetrate clouds No reliable indicators of biomass in closed canopy structure	Consistent global data Small to large scale mapping Free
	Fine < 5 m (e.g. Quickbird)	R^2 value 0.75 and predictive error of 27%	Need large data storage and processing time High cost (cost arise with increasing area)	Estimate tree crown size Validation at localized scale
	Hyperspectral, many, very narrow, contiguous spectral bands (e.g. ALOS)	R^2 value 0.83 and predictive error unknown	Cloud cover High cost Saturation in dense canopy Computationally intensive and technically demanding	Allows species level discrimination Integration with LiDAR can improve results Future potential
Radar	Microwave/radar (e.g. ALOS PALSAR)	R^2 value 0.74 and predictive error of 25%	Not accurate in mountain regions Saturation at high biomass density Low spatial resolution (AGB estimations for species level inaccurate) Cannot be applied on any vegetation type without considering stand and ground conditions	Vertical structure Can penetrate clouds Can be accurate at low biomass density Integrating Radar with multisource data is a promising approach
LiDAR	Laser light Spatial resolution 0.5 cm-5 m (e.g. Carbon 3D)	R^2 value 0.89 and predictive error of 14%	Can't penetrate clouds Requires extensive field data calibration Repetitive at high cost and logistic deployment Technically demanding Highly expensive	Accurate for estimating forest biomass in all forest types Potential for satellite-based system to estimate global forest carbon stock 3D

8 Soil sampling for carbon stock quantification

Soil organic carbon stock estimation is challenging, because soil carbon content and soil biochemical processes vary greatly spatially and temporally. Physical sampling can be used for baseline determination and monitoring SOC stock changes. Soil sampling should be well planned and fulfil standard methodology criteria. Several environmental factors cause heterogeneity in the organic carbon content in soils and standardization adds confidence in sampling results (FAO 2019). For example, 60% of carbon in boreal forests is located in soil (Liski et al. 2006) and changes in this pool are small in relation to the size of the stock, which means that forest soil carbon stock changes are hard to measure and detect reliably (Peltoniemi et al. 2004).

The conventional approach to determine soil organic carbon quantity is to collect soil samples and analyse them for carbon concentration. This procedure includes field soil sampling, sample preparation and laboratory analysis. Dry bulk density measurements are also required to convert concentration from mass to volume based (Whitehead et al. 2012). Soil dry bulk density is the dry mass per unit volume of the soil. Soils include solids and pores, and those pores can contain air, water or both and bulk density typically has high spatial variability (Wild 1993). Soil carbon concentration can be determined with dry combustion. Dry combustion is done with standard automatic instruments in a laboratory. Bulk density is conventionally measured with the volumetric ring method or the clod method (for soils with many rock fragments) (England and Viscarra Rossel 2018). Due to the soil characteristics the direct soil sampling needs to be considered thoroughly in order to achieve effective and representative sampling (FAO 2019).

Soil sampling can be carried out in arable and forest soils, and every soil type. Forest soil sampling is more complicated than sampling of cultivated soils, but there are approaches that are suitable for soils under different vegetation types (grasslands, trees, wet peat etc.) (Whitehead et al. 2012). Forest soils typically have well-developed organic layers and high organic matter content, which causes significant variations of SOC with depth. Compared to agricultural soils the spatial variability is usually larger in forest soils (IPCC 2003, Vanguelova et al. 2016).

8.1 Sampling design and dry bulk density

Sampling size and core depth depend on the purpose of the sampling, and vertical and horizontal stratification or heterogeneity of soil carbon. If the purpose is to estimate the total amount of soil organic carbon stock in a certain area, then the sample collection should contain all subunits in that location (Whitehead et al. 2012). If the land area is shallow mineral soil with organic horizon, then the sampling of multiple cores should be distributed accordingly. Slopes also need several sampling points in different slope positions. In general, that the larger the horizontal or vertical gradient, the larger the replicate needed. The horizontal gradient affects the number of cores and the vertical gradient affects the number of the samples collected in each core (Whitehead et al. 2012). Sampling locations for soil coring should be randomly determined to avoid bias. GPS coordinates of each sampling location should be recorded for future revisiting (FAO 2019).

Soil samples are collected from certain soil depth and most often soil sampling for carbon stock estimation purposes is done in a depth of 30 cm, the minimum recommended (FAO 2019). Deeper layers of soil can also be sampled in the depths of 30−60 cm and 60−100 cm. The 100 cm sampling depth often requires specific machinery (Smith et al. 2020). Large amount of SOC is found under 30 cm depth, it is estimated 60% of SOC locates deeper layers (Soussana and Lemaire 2014). Long-term SOC stabilization may occur in deeper layers and short term SOC changes happen in top layer (Conant et al. 2001), which makes it important to also sample soil layers below 30 cm (Jobbagy and Jackson 2000). A sample can be collected by using a soil corer tool of known volume, or a pit. A large pit is more time consuming but reveals the whole soil profile and reduces uncertainties related to soil compaction. Soil coring with suitable tool and the pit are both accepted practices; most important is to use such methods that the needed parameters can be calculated/estimated (e.g. soil bulk density, soil mass) (FAO 2019).

Soil coring is usually conducted with a simple cylinder, which is pressed into the soil, to the depth of interest. FAO recommends that the core diameter is something between 50 and 100 mm. This is because a diameter smaller than 50 mm gives a small sample volume that makes it difficult to represent properly the coarse roots and coarse mineral fragments. Diameters larger than 100 mm are difficult to handle (FAO 2019). Depending on the

depth of the core, the sample might be divided into sections. According to the method from Blakemore et al. (1987), the fresh sample is weighted (each section if necessary), sub-sampled and homogenized. Dry mass is calculated from the water content and field weight, and bulk density is determined by dividing the dry mass by its volume (each section). Soil fraction is sieved, and soil that passes 2 mm sieve and the organic carbon in it, is the internationally accepted definition of operational SOC (fine earth fraction) (FAO 2019).

Compositing is a procedure where several soil cores (subsamples) are pooled together into one homogenous composite sample. This method is also known as bulking. In those samples, SOC concentration should be equal to the average SOC value of individual cores. Compositing method can be used for reducing spatial variability and overall cost from multiple soil sample analyses (FAO 2019).

8.2 Soil organic carbon content and stock size determination

Dry combustion is an analytical method to measure organic carbon content in soil. In dry combustion, finely grounded soil samples are burned generally around 1000 °C (Nelson and Sommers 1996). Pure oxygen acts as a catalyst or accelerator and ensures complete combustion of the sample. Other catalysts are vanadium pentoxide, copper (Cu), copper oxide (CuO) and aluminium oxide (AlO) (FAO 2019). The end product, $CO_{2,}$ is then quantified by gas chromatography. Since all carbon units are measured, it is important to remove other carbonates (SIC) before SOC determination. This is conducted with hydrochloric acid acidification prior the analysis. Some soils include high amounts of highly stable organic carbon compounds (e.g. char from natural fires and biochar) which don’t decompose in temperatures under 600 °C (FAO 2019). This may lead to underestimation of SOC concentration (Nelson and Sommers 1996). Other analytical methods are also available (e.g. wet digestion/oxidation) (Vitti et al. 2016.).

For SOC stock determination, soils fine earth and coarse mineral fraction, organic carbon concentration in the fine earth fraction and soil bulk density or fine earth mass are necessary parameters. Those parameters can be used in equation 6 to calculate SOC stock (FAO 2019).

$$SOCi\ stock\ \left(\frac{Mg\ C}{ha}\right) = OCi \times BDfine\ i \times (1 - vGi) \times ti \times 0.1 \quad (6)$$

in which

SOCi = soil organic carbon stock (in Mg C /ha) of the depth increment i

OCi = organic carbon content (mg C g/soil) of the soil fraction (< 2 mm) in the depth increment i

BDfine I = the mass of the ne earth per volume of ne earth of the depth increment I (g ne earth cm-3 ne earth = dry soil mass [g] – coarse mineral fragment mass [g]) / (soil sample volume [cm3] – coarse mineral fragment volume [cm3])

vGi = the volumetric coarse fragment content of the depth increment i

ti = thickness (depth, in cm), of the depth increment i

0.1 = conversion factor for converting mg C cm^2 to Mg C/ha.

When SOC stock changes are monitored, changes in bulk density should also be considered. Because of bulk density variation, comparison of SOC stocks should be made on an equivalent soil mass basis (ESM). This means that SOC stocks over time are compared to the same mass of soil. This method fixes the effect of SOC content and bulk density variation in different soil depths (Wend and Hauser 2013). Overall, SOC stock determination should always be conducted with the same sampling and analyzing protocol, so that changes could be detected reliable (Heikkinen et al. 2020). Davis et al. (2018) compared soil organic carbon measurement protocols in U.S. and Brazil and they found out that reported procedures reflected big variabilities, which makes it hard to compare results from different study sites. Differences may be due to different sampling protocols instead of differences in soil carbon stocks.

8.3 Minimum number of sampling points

A long monitoring period and a large sample size are needed for evaluating soil treatment effects on SOC (due to large spatial variation of SOC). The smallest difference in SOC stock that can be detected and is statistically significant, is based on the minimum detectable difference (MDD), and it can be determined through power analysis (equation 7) (Zar 1999).

$$MDD \geq \frac{S}{\sqrt{n}} \times (t_{\propto,v} + t_{\beta,v}) \quad (7)$$

in which

MDD = minimum detectable difference

S = standard deviation of the difference in SOC stocks between t_0 and t_1

n = number of replicates

v = n – 1 is the degrees of freedom for the relevant t-distribution

t = values of the t-distribution given a certain power level (1-β) and α level.

The minimum number of samples needed to detect the difference of two different sampling points can be calculated with equation 8 (Vanguelova et al. 2016).

$$n \geq \left(\frac{S \times (t_{\propto} + t_{\beta})}{MDD}\right)^2 \quad (8)$$

in which

n = number of samples,

MDD = minimum detectable difference

S = estimated standard deviation,

t_α = two-sided critical value of the t-distribution at a given significance level (α) frequently taken as 0.05 (5%)

t_β = one-sided quartile of the t-distribution corresponding to a probability of type II error β (e.g. 90%).

There are different calculation methods, and for example Mäkipää et al. (2008) used the equation 9 to calculate the number of plots needed for detection of soil carbon stock changes in Finnish forests.

$$n = \left(t \times {}^{s}/_{E}\right)^{2} \qquad (9)$$

in which
n = number of plots required
t = value from Student's t distribution table (number of degrees of freedom and confidence interval considered)
s = estimated standard deviation
E = desired half of the confidence interval.

Schrumpf et al. (2011) took soil samples from 12 sites from CarboEurope Integrated Program across Europe to find out sufficient core number in plot/field scale and if the equivalent soil mass method would increase the smallest detectable change. They took 100 sampling points per site (up to 60 cm depth) and they covered the major land use types, deciduous and coniferous forests, grasslands and croplands. The authors concluded that in cropland sites the spatial variability was smallest which also led to the lowest minimum detectable difference (105 ± 28 g C/m^2). In grasslands the minimum detectable difference was 206 ± 64 g C/m^2 and forest sites 246 ± 64 g C/m^2.

Heikkinen et al. (2020) concluded that in boreal agricultural mineral soils the required sample size to detect difference of 0.1 kg C/m^2 at field level is several hundred samples. Median results from power analysis varied from 623 samples in coarse soil under perennial plants to 891 samples in fine soil under annual plants.

8.4 Soil sampling frequency

A single re-sampling would not distinguish any interannual variability and long-term trends. Repeated soil inventories during a certain period would be advisable, instead of just one re-sampling after several years. More frequent sampling will increase precision (Schrumpf et al. 2011). SOC change between two sampling points should be greater than

MDD, which means that if the expected stock change rate is low, the sampling time is also less frequent. Carbon input, climate and seasonal weather influence on the carbon gained or lost. Under variable environmental conditions, a longer sampling frequency is needed, to ensure that any changes in SOC stocks can be detected (FAO 2019). Intra-annual variation is also important to consider. SOC decomposition is mainly moisture and temperature dependent (Paul 2007), farming practices, carbon inputs, and carbon inputs due to natural reasons vary seasonally. Repeated sampling over several years should be planned to minimize intra-annual variation; this can be done by ensuring that sampling is conducted during the same season or by comparing more than two years (van Wesemae et al. 2010).

Smith (2004) studied the increased carbon input effects on the SOC stock change detection between two sampling points, and reported that when the C input increased by a maximum of 20 to 25%, changes in SOC stocks could be detected after 6−10 years (with 90% confidence) (Smith 2004). Schrumpf et al. (2011) also found out in their vast soil monitoring study (mentioned above) that general trends in soil organic carbon indicate that with 100 samples (per site), the change would be detectable after 2−15 years (10 cm depth). In a depth of 30 cm, the time varied between 7 years (grasslands) and 14 years (croplands, conventional farming methodologies) to 20 years in forests (Schrumpf et al. 2011).

8.5 Uncertainties in soil sampling

Soil sampling includes several steps and each step includes possible error sources. Table 7 summarises the systematic error sources at different scales. Identifying different potential sources of uncertainties is important when considering the possibilities to reduce them. Biggest problem based on literature can potentially be to neglect bulk density determination. Adequate sampling depth is also under debate (Vanguelova et al. 2016).

Table 7. Possible soil sampling error sources at different scales. Modified from Vanguelova et al. 2016.

Sample	Bulk density is not assessed Samples are not homogenized Different analytical procedures Coarse fragment volume is not assessed Different soil horizons and layers are not separated accurately Inappropriate time for soil sampling
Profile	Sampling at not full soil depth Sampling by horizon versus soil depth
Plot	Bulk density and stone content not analyzed Not enough sampling points Different sampling schemes Small scale variability not accounted Measurement error including sample preparation Not harmonized inventory teams
Landscape/National/ European	Lack of local and regional representativeness of sampling plots Important areas are underrepresented (e.g. peat soil) Lack of forest cover maps and accurate soil/hydrology maps

An appropriate scale related to carbon stock monitoring is important to define. Different scales could include profile, plot, forests, catchment, national or wider areas. Soil heterogeneity and spatial variability are important to take into consideration, as the factors are clearly scale dependent (Goidts et al. 2009). In general, soil properties vary more with increasing study area. According to Hobley and Willgoose (2010), soil carbon's spatial variability can rise sevenfold when scaling up from a point sample to landscape scale. This can lead to high uncertainties in SOC stock calculations if scaling up is not considered accordingly (Vanguelova et al. 2016).

8.6 Soil sampling costs

Mäkipää et al. (2008) calculated the sampling costs for plot scale soil sampling in Finnish forests. Costs of soil sampling depends on several factors and those costs can be divided into fixed and variable components. Fixed components include costs that are not dependent on the number of the soil samples (*n*). For example, direct personnel costs from transportation, accommodation and driving time to the sampling site (salary). Variable costs are dependent on the sample size (*n*) and it includes the costs of soil sampling, sample preparation and analyses in the laboratory (salary and all other costs). According to Mäkipää et al. (2008) measuring the carbon in soil organic layer costs 520 €/plot with 10 analyzed samples. In this study and with their sampling protocol the minimum detectable change was >860 g C/m^2, which is not very good precision. If sample size per plot was increased to 30 sampling costs arise to 1100 € and detectable change drop to 540 g C/m^2. In Peltoniemi et al. (2004) study, the organic layer in forest increased in average by 47 g C/m^2 during a 10−year period and this relatively slow change makes it hard and costly to detect on a small scale.

Singh et al. (2012) calculated how much would cost to measure field level soil carbon stock size in cropping field in Australia. They concluded that sampling to 30 cm depth in a 68−hectare area with < 2 t/ha standard error, the cost would be 2500 AU$ (~1500 €).

9 Modelling of soil carbon stocks

Soils are very heterogeneous, and it would take a large number of direct measurement samples to estimate the size of the soil carbon pool reliably. Changes in soil carbon pools occur slowly and monitoring it is often difficult (Mäkipää et al. 2004). Modelling soil dynamics and simulating stock changes helps to tackle those obstacles and offers a mathematical way to estimate SOC (Peltoniemi et al. 2007, Paustian et al. 2019). A completely accurate model is, however, difficult to develop, because the large uncertainties in empirical data and the complexity of the carbon turnover process in soil (Peltoniemi et al. 2007).

9.1 Three levels of soil models

FAO (2019) categorizes soil organic matter models into three levels according to different models of approach. These categories are 1. empirical models, 2. soil process models and 3. ecosystem models. Model categorizing varies, and for example Paustian et al. (2019) divides models that predict SOC changes into empirical models and process-based models.

Empirical models represent the observed relationship between carbon stocks and environments. Empirical models are based on statistical relationships and describe how environmental and management variables interact with SOC stocks and SOC stock changes (FAO 2019, Paustian et al. 2019). Statistical relationships are estimated from field experiments, where SOC changes due to environmental and management variables are observed (Paustian et al. 2019). Temperature, precipitation, soil clay content and land use are typical variables affecting SOC changes and empirical model development (FAO 2019). Best known empirical approach is the model developed by Intergovernmental Panel on Climate Change (IPCC) to estimate SOC stock changes for the national greenhouse gas inventories (IPCC 2003). Empirical type of approach has been the basis for more complex models (FAO 2019). The drawback of using empirical models is that typically these equations are generated for specific soil types, climates, management and carbon inputs which leads to the situation that models are not working adequately when those variables change (FAO 2019). Other limitation is lack of field experiment data from many climates, soil types and management combinations (Paustian et al. 2019). Empirical models developed by IPCC (2003) are developed from global data sets, and they are intended for national scale application. Thus, regional or local scale SOC stock estimation need new estimations of parameters used in models (Paustian et al. 2019).

Process-based models are models that estimate the SOC stock changes aided by SOC dynamics through time. These SOC dynamics consider the effects of climatic and soil factors with land use and management variables (Paustian et al. 2019, Senapti et al. 2014). These models are more detailed, and they determine SOC stocks and changes by using mathematical functions (sets of different equations), where physical and chemical soil processes are considered (FAO 2019). These models are usually constructed from several compartments (Fig. 8) where each represents the fraction of SOC with similar

characteristics. Decomposition rate and mechanism driving carbon stabilization are typical factors directing model compartment division (Stockmann et al. 2013). The carbon flow moves from litter to the microbial pool and then to more stable soil carbon pool. Moving from first compartment to next, the stability of soil organic carbon increases (FAO 2019). Yasso (Liski et al. 2005) and RothC (Coleman and Jenkins 1996) are examples of process-based models (table 8). FAO recommends that these types of models should be used when required (model specific) data is available.

Most models are developed for research purposes where aim was to study how different changing variables affect SOC dynamics. Under interest has been how SOM functions with environmental variables, edaphic variables and land-use and management practise. Process models integrate these factors and controls affecting decomposition and organic matter stabilization in soils (Paustian et al. 2019). Even tough dynamic process-oriented models might be quite comprehensive, they don't include all important ecological processes affecting soil carbon. Some exclusions might include e.g. biomass growth and nutrient cycle (FAO 2019). Process-oriented models also need relatively few data requirements. Information about climate, soil and productivity are typical data requirements for simulations (FAO 2019). Process based models can be further develop by integrating models with several data sources (Campbell and Paustian 2015) like flux measurement networks and exciting long-term field experiment (Harden et al. 2018)

Ecosystem models present the third level of modelling according to FAO (2019). Ecosystem models simulate carbon stock changes in time, considering the same factors as the level two models, but they also integrate above- and belowground plant biomass growth and carbon inputs, water and nutrient dynamics and their interactions. CENTURY (Parton et al. 1987) is one of the existing ecosystem models used for SOC estimations. Models with several compartments, processes and interactions to simulate, need higher amounts of soil, climatic and management data. Higher complexity can provide higher accuracy, but great data requirements can be difficult to obtain, which limits the application (FAO 2019).

More than 250 models describing soil carbon turnover (Manzoni and Porporato 2009) have been formulated, each for different purposes. Models differ from each other based on the biochemical and physical processes and the underlying assumptions. Table 4

summarises examples of commonly used named models. Yasso (Liski et al. 2005) and RothC (Coleman and Jenkins 1996) are process based models, CENTURY (Parton et al. 1987) is ecosystem model and FullCAM (Richards et al. 2004) is combination model which integrates several different models into one full ecosystem model.

Table 8. Overview of different types of process-oriented models. Yasso and RothC are process models, CENTURY is ecosystem model and FullCAM is combination of several models (Parton et al. 1987, Coleman and Jenkins 1996, Richards et al. 2004, Liski et al. 2005)

	Model name			
	Yasso	**RothC**	**CENTURY**	**FullCAM**
Short description	Dynamic soil carbon model. Simulates decomposition of organic matter.	Models the turnover of organic carbon	Ecosystem model. Simulates different plant-soil systems C, N, P and S dynamics in a long term.	Ecosystem full carbon model. An integration of biomass, decomposition, soil carbon models and accounting tools.
Land use area	Forest	Crop, forest, grassland	Grassland, forest, crop, savanna	Forest, crop, agroforestry
Input variables	1) Soil C stock beginning, 2) C input to soil, 3) climate	1) monthly rainfall, 2) monthly open pan evaporation, 3) average monthly mean temperature, 4) clay content of the soil, 5) an estimate of the decomposability of the incoming plant material (the DPM/RPM ratio), 6) soil cover, 7) monthly input of plant residues, 8) monthly input of farmyard manure and 9) depth of the soil layer sampled.	1) air temperature (monthly average maximum and minimum), 2) monthly precipitation, 3) lignin content of plant material, 4) plant N, P, and S content, 5) soil texture, 6) atmospheric and soil N inputs and 7) initial soil C, N, P and S levels and 8) litter or crop residues	All that: forest physiological growth model 3PG, the carbon counting model for forests CAMFor, cropping and grazing systems CAMAg, the microbial decomposition model GENDEC and the Rothamsted Soil Carbon Model RothC require.
Time step	Year	Month	Month	?
Depth	1 m	0-20 cm (topsoil)	0-20 cm (topsoil)	0-20 cm (topsoil
Ref.	Liski et al. 2005	Coleman and Jenkins 1996	Parton et al. 1987	Richards 2004

9.2 Soil carbon turnover models internal structure

According to Batlle-Aguilar et al. (2011) SOC turnover models can be divided into categories based on their internal structure. Processes-oriented (multi-compartment) (Smith et al. 1998), organism-oriented (Post et al. 2007), cohort (describes decomposition as a continuum) and a combination of the first two, are four categories that each describe SOM dynamics models (Batlle-Aguilar et al. 2011).

Process-oriented, or compartment models, are built to consider SOM transformation and migration through different soil layers (Smith et al. 1998) (Fig. 8). A compartment refers to different fractions of SOM that each have different chemical and physical characteristics. These kinds of models can be complex, including multiple compartments, or a simple one compartment, or even no compartment models, where degradation is assumed to be a continuum (Smith et al. 1998). Process-based models can be combined with Geographical Information Systems (GIS), which adds benefits for regional-scale studies. CENTURY (Parton et al. 1987) and RothC (Coleman and Jenkins 1996) are process-based models combined successfully with GIS (Batlle-Aguilar et al. 2011). As a downside, theoretical compartments created to describe SOM dynamics are difficult to compare with actual measurements of soil fractions. Thus, validation and testing are quite limited leading to a situation that model can include an undefined inaccuracy (Batlle-Aguilar et al. 2011).

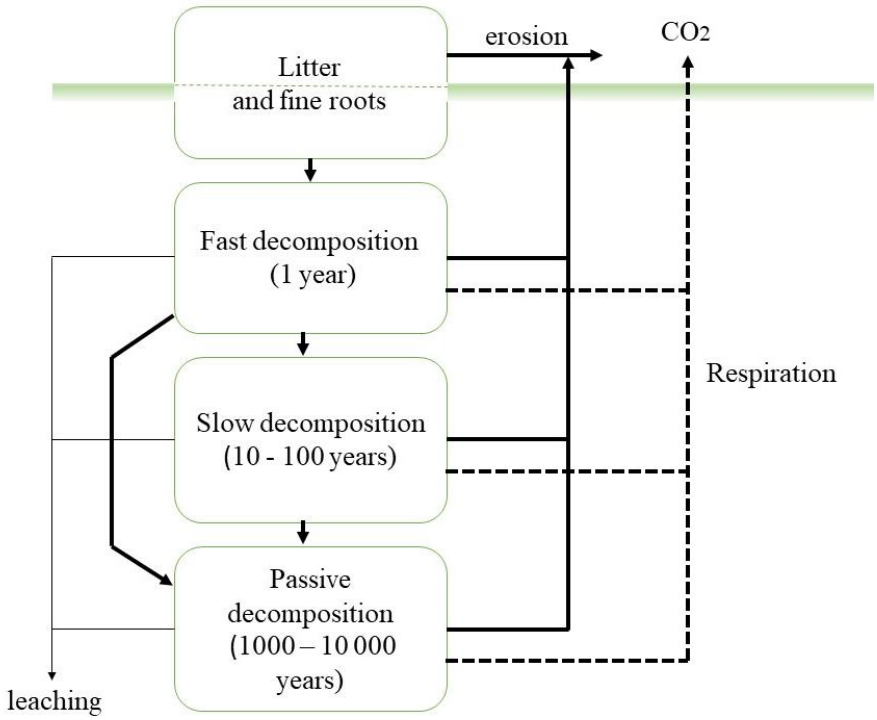

Figure 8. Separation of the SOM in different compartments representing different decomposition rates. Modified from Willgoose (2018).

Organism-based models describe SOM movements between pool, and each of these organism pools is classified. The main drivers (microbes and fauna) of SOM fluxes and transformation are explicitly accounted for, which gives more accurate estimations where the model is based on (Post et al. 2007). Accuracy is the main advantage and the negative side is that the relationship between the abundance of soil biota and degradation rate of organic matter is not yet commonly agreed upon. Another downside in organism-oriented models is that site-specific calibration requires the characterization of the whole soil microbial pool with complex techniques. Compared to process-based models, the relationship between degradation rate and substrate concentration is well known (Batlle-Aguilar et al. 2011). First-order kinetic rate (assumption: the bigger the concentration, the bigger the decomposition rate) (Senapati et al. 2014) is simple and often a suitable way to describe the organic matter transformation. Rate of these reactions can be determined in a laboratory (e.g. litter bag) and then used in process-based models, but organism-oriented models need complex site-specific calibration. Process-oriented models are more popular because of their usability (Batlle-Aguilar et al. 2011).

Cohort models divide the organic matter in soils into cohorts, and further into different pools (Senapati et al. 2014). In a cohort model, the microbial physiology is considered to be the main driving factor in organic matter decay. The fourth group of models is a combination of the process- and organism-oriented models, which have high specific data requirements and thus not commonly used (Batlle-Aguilar et al. 2011).

In most soil carbon models the size of the microbial pool (microbes, fungi and fauna) is not determined, but the decomposition is considered by variables that affect the microbial activity (e.g. temperature and soil moisture) (Peltoniemi et al. 2007). This means that the microbial activity in model is expressed as decomposition rate of compartment (Peltoniemi et al. 2007). Because SOM is complex and includes fractions of different stability, the energy needed for decomposition varies also (Davidson and Janssens 2006, Peltoniemi et al. 2007). In model compartment development, these different decomposition rates and needed energy requirements are approximated and divided to several different compartments that differ in organic matter turnover time (Peltoniemi et al. 2007). Because of the complexity of SOM, several studies confirm that simulation of carbon dynamics cannot be adequately approached with one compartment only (Kätterer et al. 1998, Davidson and Janssens 2006), but more complex SOM models, with several pools, are necessary when modelling carbon concentration changes in soils and the atmosphere (Schimel et al. 1994). Large soil carbon stocks located in slow turnover pools in soils and fluxes represent the fast turnover carbon pools (Fig. 7). Models with one pool and one turnover rate will overestimate the carbon response because changes in the stabile stocks happen in the slow pool (Telles et al. 2003)

9.3 SOC model scales

SOC models can be formulated to different scales. According to Campbell and Paustian (2015) three commonly used scales are microsite, ecosystem and global. Each scale has its own limitations and use. Microsite is the smallest scale and models designed for that can be used, for example, to predict short-term and small changes. Microsite presents, for instance, a small area of a rhizosphere. These small-scale models are difficult to link into larger scale dynamics and microsite models are also dependent on specific soil

fractionation method (a method where different soil organic matter particles are fractioned from each other) (Campbell and Paustian 2015).

Ecosystem scale models can be used to model a hypothesis based on mechanistic or empiric relationships and predict impacts of changes specific to a certain site. Ecosystem scale limitations are required for site-level data, and on this scale, models cannot represent mechanistic relationships that are important in smaller scales. RothC (Coleman and Jenkins 1996) and Yasso (Liski et al. 2005) are examples of ecosystem scale SOM models. SOM models can also be formulated on a global scale. Global scale SOM models that can be used to model hypotheses of large-scale dynamics, simulate global scenarios and predict climate change with dynamic soil feedback (Campbell and Paustian 2015).

The scaling decision is a critical component of the simulation of soil carbon for inventory purposes (Peltoniemi et al. 2007). Input data and model application will determine to which scale the soil carbon stocks can be estimated. Many models are developed to cover a small spatial resolution and a short time period (daily time step), but those models can be scaled to a larger resolution. Scaling-up can create biases, Ogle et al. (2006) concluded that increasing model spatial resolution with coarser-scale parameters can lead to significant biases. Rescaling is possible but should be done with careful consideration of the uncertainties (Peltoniemi et al. 2007).

9.4 Model selection

The choice of modelling approach depends on the purpose, available resources and expertise. FAO (2019) recommends that a locally validated model should be preferred. Internal model calibration, with region(site)-specific data, and factors adapted to that give more accurate results (FAO 2019).

Models need several types of data and data availability is an important factor when deciding which approach to use (Bellocchi et al. 2010, FAO 2019). Several different process-based models could be used for soil carbon inventories, but the selection is constrained by the availability of model input and evaluation data (Peltoniemi et al. 2007). Data sources can be, for example, national forest inventories (NFI), soil samplings and remotely sensed data. There are several international soil and climate databases that

provide data for model inputs (e.g. FAO Global Soil Information Carbon Map, Solid Grids- Global Soil Data Facility). These databases do not provide data for all situations, but in some cases local data may be available (Peltoniemi et al. 2007). National forest inventories are also widely conducted in several countries (Tomppo 2014).

Typically soil carbon models need input data, parameters and test data (FAO 2019). Input data is data that a model needs to output predictions. Most typical input variables are temperature, moisture, soil texture and nitrogen. Those are the main factors affecting the decomposition processes (Peltoniemi et al. 2007). Information about land management and disturbances are also key model inputs, because minor changes in land-use may lead to major changes in soil carbon (Peltoniemi et al. 2007). Thus, forest inventories with land use surveys, remotely sensed data and long-term soil surveys are important data sources. Data from several sources also helps up-scale models (FAO 2019, Paustian et al. 2019). Amount and coverage of biomass, species composition, topographic position, temperature and thermal regimes and edaphic characteristics are important factors and data sources that provide information on different scales are needed when plot level data is scaled over large areas. Long-term experiments give valuable information and measured data can be used to calibrate, validate, evaluate and compare models (Peltoniemi et al. 2007, FAO 2019, Paustian et al. 2019). Measurements are also needed for model development and more extensive data gives better building blocks for new models (Paustian et al. 2019). SOC models are usually used in larger, ecosystem scale, carbon change simulations and future predictions (as it is possible to formulate site-specific calibration) (Peltoniemi et al. 2007). Parametrization is a critical step in the model development. If parameters are not sufficient, new values might need to be measured or parameters to be fitted with existing calibration data (Bellocchi et al. 2010, FAO 2019). Test data is the data that the model has predicted (e.g. SOC stock and changes) and it can be divided into calibration data and validation data. Test data is used to test model outputs (FAO 2019).

Most commonly used SOC models (e.g. RothC and CENTURY) are developed for temperate climate, which means that they are parametrized and calibrated with data that fits in certain conditions. For tropical and subtropical applications, these models should be validated for conditions corresponding area under interest (Campbell and Paustian 2015).

9.5 Uncertainties and sensitivity analysis

There are several possible sources of uncertainties in SOC models. Some errors in SOC models are not avoidable because they arise from problem that man can't exactly describe complex chemical, biochemical, physiological and biological systems in a mathematical way. In general, there are two main sources of uncertainty: model uncertainty (mentioned above) and uncertainty of modelled system inputs (FAO 2019). Model uncertainties includes parameter value uncertainty, which means that the correct value of the parameter that determine the model estimations is imprecise. Modelled system inputs include measurement errors and natural variability (Ogle et al. 2010). According to (FAO 2019) structural uncertainty is the one which causes major difficulties, because if the processes are not adequately represented, no effort will not reduce the uncertainties.

Sensitivity analysis (Fig. 9) is a useful tool to identify the most significant variables and parameters for further analysis (FAO 2019). FAO (2019) recommends that model sensitivity analysis and uncertainty assessment is conducted for every simulation scenario to confirm that model is suitable for its application. Information about model inputs and processes is also important to evaluate continuously.

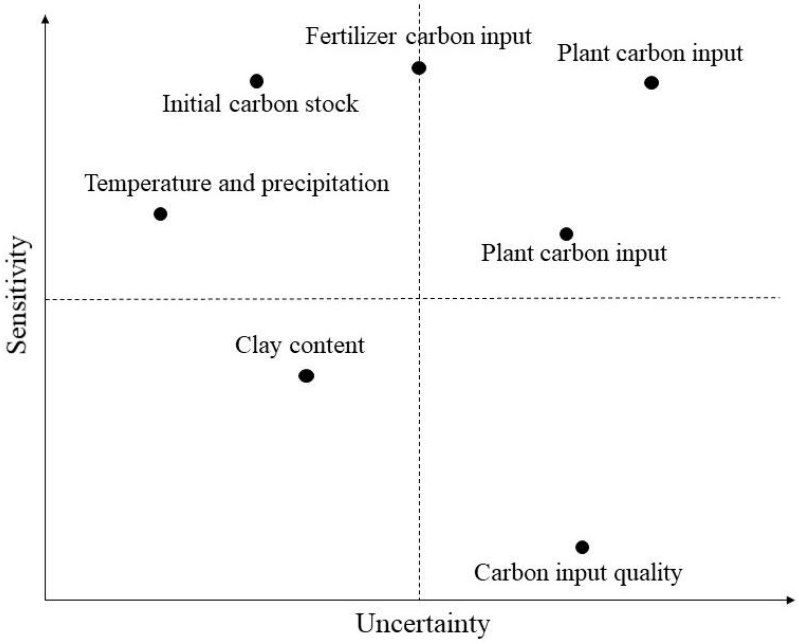

Figure 9. Illustrative figure of model (RothC) uncertainty and sensitivity presented with typical parameters needed to simulate carbon turnover. In this figure, plant carbon input

is a parameter that has high uncertainty and high model sensitivity, which makes it problematic (modified from FAO 2019).

Models should be calibrated to reduce uncertainties. Calibration can be conducted by calibrating model parameters that are most effective for the model performance (FAO 2019). Site specific calibration means that the simulation of SOC dynamics in a certain area requires calibration with data specific to that soil area, like soil particle size distribution, pH, soil type, decomposition rate, etc. This kind of information input makes models more reliable, but it complicates the prediction of changes. To truly predict SOC changes, a model should be able to simulate dynamics without site-specific data input (Smith et al. 1997). If models that need site-specific calibration are used in long term simulations, it may cause major biases in the results if the site changes over time (Willagoose 2018).

9.6 Model performance

SOC model's performance can be studied by comparing values from simulations to actual measured values from long-term field experiments (Smith et al. 1997). Commonly used measures of model performance are the coefficient of determination (R^2) and root mean square error (RMSE) (FAO 2019). Smith et al. (1997) compared the performance of nine different SOM models. A model's performance was evaluated with different data sets (arable land, forest soil, strong fertilization, etc.) and the results were compared to soil samples (from long-term soil inventories). All nine were process-oriented multicompartment models. From those nine models, RothC (Coleman and Jenkins 1996) and CENTURY (Parton et al. 1987) were the most interesting ones considering carbon dynamics. RothC (Coleman and Jenkins 1996), CENTURY (Parton et al. 1987) did not show significant biases in overall simulations and they performed the best in all datasets. RothC (Coleman and Jenkins 1996) and CENTURY (Parton et al. 1987) can be used in different land-use areas, which explains partly their good performance. One source of error occurs if a model is used in an application for land-use where it was not developed. For example, SOMM model is developed for forestry/grassland and when it is used to simulate soil organic carbon in arable soils, it is forced to count grass as the only crops. That kind of structural problem causes errors because it is well documented that different

plant species and management practices result in different SOC accumulation and should be considered in simulations (Smith et al. 1997).

Smith et al. (1997) also tested the performance of combined models and concluded that the coupling of two models does not lead to more accurate results. On the contrary, it led to inaccurate values and estimations with more errors.

Heikkinen et al. (2014) compared Yasso (Liski et al. 2005) and RothC (Coleman and Jenkins 1996) to measured carbon values. Mineral soil carbon stock changes were simulated after the cropland conversion to grassland. The study area soil type was mineral soil and the total area was 4 hectares. The soil sampling was conducted in 1980, 1999 and 2004, and the sampling depth was 0−20, 20−40 and 40−60 cm. Soil C stock (equal to C content x bulk density) was determined to the depths 20 and 60 cm. The concluded result was that Yasso07 and RothC both estimated the carbon stock increase relatively accurately (R^2 0.60 and 0.72 respectively). Yasso07 underestimated the change in soil C stocks and RothC overestimated the changes.

10 Sensing soil organic carbon

Spectroscopic techniques rely on the interaction of electromagnetic radiation and matter (Carcia-Sanchez et al. 2017). Spectroscopic technique has many advantages over the traditional soil sampling methods, as it is a non-destructive analysis method, do not require toxic or expensive chemicals, is fast, measures several parameters in a single analysis and can be used *in situ* or in a laboratory (Carcia-Sanchez et al. 2017). Spectroscopic laboratory devices are accurate, but even they enable analyzation of larger amount of soil samples more rapidly than dry combustion method (England and Viscarra Rossel 2018), they still require field sampling and some sample preparation before analysis, which are laborious. Proximal soil sensing is method where field-based instruments are used (England and Viscarra Rossel 2018).

Soil organic carbon quantity can be measured by different sensors relying on electromagnetic radiation because soil matters organic bonds and minerals absorb light in specific wavelengths. Soil information can be measured via sensors using signals that correspond to physical qualities and that information can be linked to soil properties. Soil

content specific absorbance spectrum can be compared to spectral measurements of known sample via statistical model (Carcia-Sanchez et al. 2017). Reference spectrum is derived from samples, which have been analyzed by traditional laboratory methods (e.g. dry combustion) (Stenberg et al. 2010).

Soil organic carbon wavelengths are mainly in the visible-near infrared (400−700 nm), near infrared (700−2500 nm) and mid infrared (2500−25000 nm) region (Smith et al. 2020). Soil spectrum can be generated by directing radiation to the sample, which makes the molecular bonds to vibrate. Vibrating molecules absorb light and eventually produces a characteristic shape that can be used for analytical purposes (Stenberg et al. 2010).

10.1 Proximal soil sensing

According to Viscarra Rossel et al. (2011) proximal soil sensing is a method where field-based sensors are used in contact or close to (within 2 m) the soil. Proximal soil sensing doesn't include remote sensing or laboratory measurements.

There are several different proximal soil sensors and they can be classified according to the manner they measure or the source of their energy. Sensors can be invasive, which means that sensor is in contact to soil during measurements or non-invasive. Invasive measurements can be done within the soil or for example excavated soils. Proximal soil sensor is active if it produces its own energy form artificial energy source and passive if they use natural radiation energy form sun or earth. Sensors can be used "on a go" or moving (mobile). Sensors can consider to be indirect or direct. Direct proximal soil sensing means that measured soil property is based on a physical process (e.g. clay minerology). However, when the measurement is of a proxy and inference is with a pedotransfer function (PTF = raw soil data translated into more useful information), then the proximal soil sensor is indirect. Proximal soil sensing is done in same spatial scale as conventional methods (soil sampling and dry composition) (Viscarra Rossel et al. 2011).

Soil sensors for field use are developed for cost-effective and rapid soil organic carbon determination. The benefit those sensors provide is that high sampling density can capture more effectively field variability and hence solve the problem with selecting a correct soil

sampling design (Sinfield et al. 2010). Proximal sensing ranges from micro to landscape (plot to farm) scale (England and Viscarra Rossel 2018)

10.1.1 Visible and infrared reflectance spectroscopy

Visible (vis) portion of the electromagnetic spectrum is 400−700 nm and near infrared (NIR) region is 700−2500 nm. Visible and infrared spectroscopic techniques are sensitive to soil organic and inorganic components. Visible and near-infrared ranges can also be combined; this synergy adds value to the sensing because both wavelength ranges provide different information about soil organic carbon (England and Viscarra Rossel 2018). Mid-infrared (mid-IR) electromagnetic spectrum region is from 2500−25000 nm and it contains more information about soil organic composition than vis-NIR (Viscarra Rossel et al. 2011).

Visible-NIR techniques have been used successfully in SOC concentration estimations on field conditions. Mid-IR can predict SOC concentration, most commonly, in a laboratory with measurements on dried and finely ground soil samples. This is partly because there are strong water absorptions in the mid-IR range. This effect tends to mask or deform other soil constituents' absorptions which makes it more difficult to calibrate adequately. Portable mid-IR devices are currently under development and some exist already (England and Viscarra Rossel 2018).

10.1.2 Laser-induced breakdown and neutron induced gamma-ray spectroscopy

Laser-induced breakdown spectroscopy (LIBS) and neutron-induced gamma-ray spectroscopy (INS) are emerging and promising techniques (FAO 2019, Paustian et al. 2019). Laser-induced breakdown spectroscopy is a technology where optically focused short-pulsed laser is used to heat the soil sample. Heating results in the formation of high temperature plasma. After the plasma is cooled down, it can be measured with spectrometer (190-1000 nm), as plasma emits radiation that is characteristics to its fragments. The plasma forms on only a very limited area allowing only a small portion of the sample to be measured during each event. Advances in fiber optic technology also makes LIBS systems portable and mobile (Viscarra Rossel et al. 2011). LIBS

measurements are rapid, in a laboratory, time per sample is less than a minute (England and Viscarra Rossel 2018).

Currently LIBS for SOC measurements are mainly conducted with benchtop laboratory devises that require sample preparation. Other constrains are sample representativeness (tiny sample volume) and limited understanding of wet field measurements accuracy (Viscarra Rossel et al. 2011).

Inelastic neutron scattering (INS) acts in the gamma ray region of the electromagnetic spectrum (Wielopolski et al. 2008, Viscarra Rossel et al. 2011). Neutron generator generates fast neutrons which penetrate the soil and interact with nuclei of the elements. In that process, gamma rays are simulated, and those rays can be detected by a scintillation detector (e.g. sodium iodide). The detector measures the spectra and from peak intensities, with specific calibrations, it is possible to determine the SOC in units of g C/m^2. INS is a non-destructive method with the capability to measure to a depth of 30-50 cm, from a relatively large footprint (diameter 150 cm) and large volumes (0,3 m^3) (Wielopolski et al. 2008). INS method requires some conventional soil sampling for correlation establishing, but once correlation is formulated there is no need for further soil sampling (Izaurralde et al. 2013). In INS technique, the sampling depth is not precisely defined, but according to Izaurralde et al. (2013) about 90% of the detected signals was from 30 cm depth and 99% effective depth was 50 cm (based on Monte Carlo calculations). This means that depth variation should not play a major role in total, since only small signal arrives from deeper layers. INS is not yet well developed, but it is known that it would suit well in field conditions.

10.1.3 Uncertainties and important issues

Reflected soil absorbance needs several processing steps (Fig. 10) before information of soil organic carbon can be interpret. Spectral analysis is based on multivariate statistical methods. Soil matrix is complicated mixture of different parameters that have overlapping absorptions and low consecrations (England and Viscarra Rossel 2018, Angelopoulou et al. 2020). These factors interfere the measurements which result to preprocessing in a purpose to for example minimize noise and enhance signals (Nawar et al. 2016).

Multivariate spectroscopic modelling is a process where sensed soil properties are related to the absorbance of a set of known reference samples. This describes the relationship between spectral data and soil properties. Most commonly used method is partial least squares regression (PLSR). Accuracy of the estimations is highly dependent on the chosen calibration method (table 6) (Angelopoulou et al. 2020). Model development need several diagnostic steps, where the model fit, and performance is evaluated and improved. Model is also validated with external data set. According to Australian Government "Measurement of Soil Carbon Sequestration in Agricultural Systems" methodology (2018) the data for the spectroscopic modelling and validation is divided into three components: training set, validation set and prediction set. Training set is used to develop the spectroscopic model and validation set is used to test the accuracy of model's estimates. Training and validation set's soil samples need to be analyzed with reference analytic method, which is in this case dry combustion, to determine their soil organic carbon concentration. After laboratory analysis data sets can be used to develop the spectroscopic model. Data from large spectral libraries can be used to expand the site-specific models and to improve the accuracy, but not to develop the model (Australian Government 2018).

In field conditions, soil moisture, surface roughness and vegetation cover affect the spectral signal (Geht and Rice 2006, Rodionov et al. 2014). For example, vegetation would lead to overestimation of soil organic carbon (Dvorakova et al. 2011).

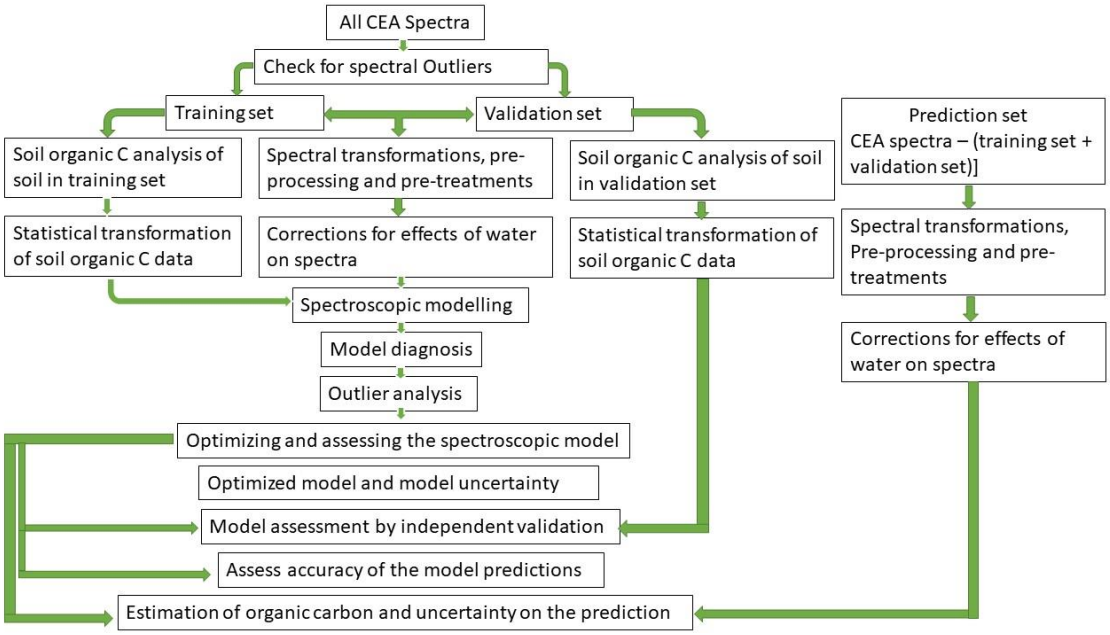

Figure 10. Flow diagram of different procedural steps of visible-infrared spectra when estimating soil organic carbon content. Closely adopted from soil carbon methodology by Australian Government (2018).

10.1.4 Accuracy and cost

Stevens et al. (2006) tested field spectroscopy in agricultural land and they concluded that according to the results, the standard error of measurements allows to detect a soil organic carbon change of 7.2−9.9 Mg C/ha (upper 30 cm of the soil). According to Freibauer et al. (2004) soil organic carbon changes result of land conversion or management practices are only 0.3−1.9 Mg C/ha/year, which means that the field spectroscopy would detect any changes in the soil organic carbon after minimum of 10 years.

England and Viscarra Rossel (2018) gathered information about accuracy and costs of different spectroscopic techniques (table 9) for soil carbon accounting. Both LIBS and INS techniques are also expensive, sensor costs are even more than 100 000 AUD (63 989 €) (England and Viscarra Rossel 2018).

Table 9. Assessment of cost and accuracy of different sensing methods for carbon determination. Modified from England and Viscarra Rossel 2018.

Method	Instrument cost (in thousands of AUD)	Measurement cost per sample (AUD)	Accuracy	
			RMSE	R^2
vis-NIR, dried ground	10−100 (6−64 €)	8 (5 €)	0.44	0.85
vis-NIR, field condition	10−100 (6−64 €)	0.8 (0.5€)	0.47	0.81
mid-IR, dried, finely ground	25−90 (16−57 €)	15 (9 €)	0.11	0.93

Cremers et al. (2001) evaluated LIBS technique's capability for soil total carbon detection. They conducted the study on agricultural soil and on woodland soil, and they concluded that LIBS instrument has a detection limit of 300 mg C /kg, a precision of 4-5% and accuracy of 3−14% (= 750 mg C/kg).

Wielopolski et al. (2011) tested INS for soil carbon pool determinations *in situ.* They concluded that INS estimations of soil total carbon amount agreed with dry combustion method values in organic soils (difference varied from 3% to 9%). In pasturelands there was no agreement between the two methods and difference varied from 16% to 168%. In organic soils, the total carbon amount varied from 3.92 to 5.36 kg C/m^2 and in pasturelands the variability was from -3.07 to 5.96 kg C/m^2.

Izaurralde et al. (2012) tested portable LIBS, INS and infrared spectroscopy (DRIFTS) methods against results from dry combustion. In their study, the soil carbon density (total carbon, not organic carbon) determined with dry combustion method was 4.07 kg C/m^2, LIBS gave estimation value of 3.27 kg C/m^2, infrared 4.32 kg C/m^2 and INS 2.57 kg C/m^2 with "universal" calibrations and 4.06 kg C/m^2 with "local" calibrations. Compared to the dry combustion method, the LIBS underestimated (20%) the carbon concentration, infrared overestimated it slightly (6%) and INS with local calibration was very accurate.

Different studies are hard to compare due the different measurement, modelling and prediction procedures (table 10). According to Angelopoulou et al. (2020) proximal soil sensing *in situ* is developed in recent years, but more research needs to be done.
carbon stocks

Table 10. Comparison of different infrared sensors and multivariate methods for soil organic matter or soil organic carbon estimations in field conditions (modified from Angelopoulou et al. 2020).

Spectral range	Multivariate method	R^2	Reference
350-2500	PLSR	0.63-0.70	Ji et al. (2015)
305-2200	PLSR	0.37-0.81	Kuang et al. (2015)
	ANN	0.39-0.90	
350-2500	PLSR	0.84	Rodinov et al. (2016)
350-2500	PLSR	0.75	Cambou et al. (2016)
350-2500	CUBIST	0.81	Vicarra Rossel et al. (2017)
350-2500	smote/PLSR	0.40-0.86	Kuhnel and Bogner (2017)
350-2200	MARS	0.76	Sorenson et al. (2017)
	ANN	0.01	
	SVMR	0.75	
	PLSR	0.54	
	RF	0.78	
	Cubist	0.8	
350-2200	PLSR	0.23-0.82	Veum et al. (2018)
305-2200	PLSR	0.74-0.78	Nawar et al. (2018)
305-2200	RF	0.12-0.75	Nawar et al. (2019)
343-2222	PLSR	0.8	Pei et al. (2019)
	NN	0.86	
	RT	0.69	
	RF	0.58	

11 Gas flux measurements with eddy covariance

The full carbon budget on the ecosystem level can be achieved with carbon flux measurements (Smith et al. 2020). Micrometeorological techniques measure the gas exchange between ecosystem and atmosphere (Rinne et al. 2016). Full carbon budget quantification needs information about carbon uptake through photosynthesis, carbon losses through respiration and other C inputs and outputs (e.g. organic amendments and harvest). Gross primary production (GPP) describes the carbon uptake through photosynthesis. When soil, plant and litter respiration (R_e) are subtracted from the GPP, the result gives the net ecosystem exchange (NEE), or net ecosystem production (NEP)

(equation 10). Net ecosystem production of CO_2 presents the whole CO_2 entering and leaving the ecosystem during time period (Smith et al. 2010).

$$NEP = GPP - R_e \qquad (10)$$

in which
NEP= net ecosystem production
GPP =gross primary production
R =ecosystem respiration.

NEE and NEP of CO_2 can be estimated with cuvettes (not included) or with the eddy covariance methods (Smith et al. 2010).

The eddy covariance (EC) is a method for measuring heat, mass and momentum exchange between the surface and the overlying atmosphere. Surface should be flat and horizontally homogenous, and under these conditions the net transport is one-dimensional. The vertical flux density can be calculated by a covariance between turbulent fluctuations of the vertical wind and the quantity of interest (Aubinet et al. 2012, Flechard et al. 2020). This means that the exchange rate of CO_2 between atmosphere and ecosystem can be determined with measuring the covariance between the vertical wind velocity fluctuations and the CO_2 mixing ratio (Byrne et al. 2007). An eddy is a current of flowing material that moves in a whirlpool or circular motion against the main current. Eddies are formed from wind, roughness of terrestrial surface and convective heat flows on the boundary layer. A boundary layer is a relatively thin layer of the atmosphere and the thickness varies diurnally and geographically (Posudin 2014).

The eddy covariance system (Fig. 11) includes three sensors that are used to measure water vapor density, air temperature and wind speed. EC measurements are typically made on the surface boundary layer (Baldocchi 2003, Aubinet et al. 2012). Fluxes are approximately constant in height on the surface layer; hence measurements taken in this layer are representative of the fluxes from the underlying surface. On the boundary layer the atmospheric turbulence is the main transport mechanism. To determine CO_2 fluxes the tower needs also analyzer for measuring turbulent fluctuations in CO_2. Commonly used analyzer is an infrared gas analyzer, with open- or closed-path configuration. Open-

path system needs more maintenance above cultivated soil because for example dust form tilling can block the equipment. Both systems include a broadband infrared light source, band-pass filter and a detector (Baldocchi 2003, Aubinet et al. 2012). When infrared light is emitted by CO_2 molecule the detector observes the reduced light intensity. This reduction presents the nonlinear function of the molar concentration of CO_2. To be able to capture eddies the air movement should be constant. Eddy covariance sampling frequency is high, usually 10-20 Hz. This is because only high sampling frequency can cover turbulent fluxes (Aubinet et al. 2012, Flechard et al. 2020). Eddy covariance measurement tower can cover large scales from hundreds of meters to several kilometers or it can be used in field scale. This sampling area is called flux footprint, and size of it depends from the objective of measurements (Byrne et al. 2007).

Fig. 11. Eddy covariance tower and power source in a grass field. Photo: Anniina Lampinen

11.1 Important things to consider

According to Aubinet et al. (2012) application of this micrometeorological technique requires vast knowledge of technical issues and the studied phenomena. There are several options for eddy covariance tower design, and some instrument options and configurations. Towers can also be placed on different sites. Installation and operational costs, and precision and accuracy are the main points taken into consideration when designing the optimal solution (Baldocchi 2003, Aubinet et al. 2012). Site design is the first step to ensure proper accuracy and precision. There is unlikely going to be a perfect design and some compromises between science requirements, costs and practicality inevitably occur. The measurement tower should be placed in an area where the systematic biases are minimized, and ecological integrity is maintained (Aubinet et al. 2012, Flechard et al. 2020). Ecosystems are structurally and functionally diverse, and all the environmental extremes can be found. Towers need to capture complex ecological drivers and processes and withstand extreme conditions like high temperature, ice and snow loading. After site is selected, site operation including calibration and validation are essential steps to make sure that overall performance is as good as possible, and associated uncertainties are minimized (Aubinet et al. 2012).

With ecosystem gas flux measurements, the effect of diurnal, seasonal and annual variation should be considered. According to Flechard et al. (2020) if eddy covariance flux measurements are used to quantify the amount of carbon that is accumulated in forests the study period should be one or several decades. This is because only long measurement period would ensure statistically significant results, because the annual stock changes are relatively small compared to the large carbon forest stock, especially if forest soil is included.

11.2 Uncertainties and accuracy

Eddy covariance methods includes several possible sources of uncertainties. According to Baldocchi (2003) when operating the most accurate results can be measured when the tower locates in flat terrain on top of homogenous vegetation which extends upwind for an extended distance surrounded by steady atmospheric conditions. But in nature conditions are not always ideal and when the method is applied over complex and natural

landscape where wind, temperature, humidity and CO_2 vary with time, the CO_2 quantification needs corrections. Long measurements period reduces the random sampling errors (Flechard et al. 2020), but long measurement time means also gaps in the data. Gaps in a long-term data can occur for example due to sensor malfunction or if the wind is coming from undesirable wind sector. Gaps in the data can be filled e.g. with empirically derived algorithms. This approach needs continuous tuning because biological factors (like leaf area, soil moisture) are changing seasonally. Nighttime fluxes need also corrections. CO_2 emitted by nighttime may not reach the tower height due the fact that during nighttime thermal stratification is stable. If nighttime CO_2 is not measured, then the system underestimates the ecosystem respiration (Baldocchi 2003.

Goulden et al. (1996) concluded that sampling error in forest study area was ±30 g C/m^2 /year and the net annual CO_2 uptake is 200 g C/m^2/year. According to Balldocchi (2003) the error bound from nearly ideal sites for annual net exchange of CO_2 is less than ±50 g C/m^2 /year (concluded from several studies). Carbon sequestration estimations from flux measurements have been relatively uncertain.

Carbon sequestration studies conducted with eddy covariance have been compared to conventional soil sampling methods. For example, Jones et al. (2017) estimated soil carbon sequestration in grasslands with soil inventories and eddy covariance flux measurements. Study period was 7 years and results showed poor agreement. Repeated soil sampling showed soil carbon stock loss average of 29.08 g C m^2 (60 cm depth) in 7 years and carbon flux budget of -179.6 g C m^2/year. Negative flux budget value means that area under interest acts as a sink, which means that in their study, the flux balance estimated that carbon was sequestrated. Disagreement might be due the underestimation of carbon exported from the field, which might lead to overestimation of carbon storage in the soils in a flux balance calculation. The authors argued that leaching of dissolved organic carbon and inorganic carbon from the field could be the variables that were underestimated. There are also studies that show comparable estimates. For example, Skinner and Dell (2015) compared carbon sequestration in pasture lands. Study period was 9 years and in their study eddy covariance showed that ecosystem act as a carbon source with rate of 103 g C/m^2/year. Soil samples showed similar trend, soil organic carbon stock decreased, depending from the soil depth, from 26 to 202 g C/m^2/year (60 cm depth 170 g C m^2/year). Ferster et al. (2015) compared carbon fluxes to carbon stock

changes estimated with forest inventories in forest sites, and their results also showed agreement between methods.

12 Carbon quantification methods used in voluntary market methodologies

This chapter provides short overview of carbon quantification methods used in current offset projects by two companies that share most of all offsets in voluntary markets. Purpose is to shortly introduce quantification methods these companies use and what are the precision requirements, to give perspective of the current state.

There are several companies, acting in a voluntary market, that provide carbon offsets via different projects and activities. This area is not currently regulated, and it lacks standards and specific project boundaries (e.g. what areas can be used for afforestation). According to Financial news (2019) Verra and Gold Standard are companies certifying 80% of all offsets. Both companies have been launched in beginning of 2000s and aim to sustainable climate actions. Companies have developed several methodologies for different natural based actions and most deposited and released credits are from forestry practices (afforestation) which are implemented in developing countries (Gold Standard 2020, Verra 2020). Each methodology includes descriptions of how different part of projects/activities are dealt.

12.1 Verra

Verra is a global company that develops and manages standards for sustainable development and climate actions. Their standards and frameworks help to channel finances to projects and activities which have high positive climate impact. Verra was founded in 2005 by specialists to fill the need for more assurance quality practises in voluntary carbon markets. Nowadays Verra manages several programs and initiatives, like VCS Program, where they turn greenhouse gas emission reductions and removals from certified projects into tradable carbon credits. This program includes different technologies and natural based solutions, including forest and wetland restoration and conversation, and agricultural land management (Verra 2020).

Verra owns several methodologies which can be implemented in different kind of projects considering forests and biomass carbon pools. The carbon pool size quantification method used in several of these methodologies is forest inventory (Verra methodologies 2020). They have developed Agricultural Land Management (ALM) methodology which was launched in October 2020. This methodology provides procedures to estimate the GHG (CO_2, CH_4, and N_2O) emission reductions and removals which are achieved with improved agricultural land management practises. Focus is on practises that help to increase the soil organic carbon storages and it can be used in a regenerative agriculture. ALM methodology provides three possible approaches:

1. Measure and Model:
   Initial SOC stock size is measured and an acceptable model is then used to estimate the change. Acceptable model needs edaphic characteristics and actual implemented agricultural practices, initial SOC stock and climatic conditions from sample fields.
2. Measure and Re-measure:
   This approach utilizes direct measurements (soil samples) in two time points, and it can be used if there are no relevant models to apply. Some regions, crops or practices may lack accurate validated and parametrized models. In October 2020 it is mentioned that this quantification approach 2 cannot be used because there is no benchmark for performance.
3. Calculation:
   CO_2 flux is calculated from IPCC Guideline for National Greenhouse Gas Inventories (2019) equations.

Verra ALM methodology sets the accuracy requirement to be precision of 15% of the mean (95% confidence level) of total SOC change calculations (Verra Agricultural Land Management methodology 2020).

12.2 Gold Standard

Gold standard for the Global Goals is standard that provides credible projects that have positive effect to climate and sustainable development. Gold Standard was established in 2003 by WWF and other non-governmental organizations. Paris Climate Agreement and the Sustainable Development Goals were the main drivers to develop a best practice standard for climate and development in a most sustainable way. Their purpose is to maximize positive climate impact and at the same time providing income possibilities for people. Their mission is: *"To catalyzes more ambitious climate action to achieve the Global Goals through robust standards and verified impacts"* (Gold Standard 2020), which means that they really emphasize that under their certification, results are trustworthy

Gold Standards for the Global Goals launched Soil Organic Carbon Framework Methodology in January 2020. This methodology introduces requirements for soil organic carbon stock and greenhouse gas emission quantification. The methodology is exerted to agricultural lands and SOC changes through better agricultural practices can be quantify with this. Gold Standard SOC methodology takes into account that data or measurements needed are not available in all projects or activities, and that's why they provide three possible approaches:

1. Direct measurements (soil samples) and directly documented baseline and size of the SOC stock.
2. Data from peer-reviewed scientific publications (modelling).
3. Default factor from the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2019) and Tier 1 and 2 approach.

With these possibilities they conclude that this methodology can be applied in a broad range of activities and with different recourses. This methodology also takes into account that science around SOC impact and activities are constantly evolving and it is not limited. Gold Standard SOC methodology sets the accuracy requirement to be precision of 20% of the mean (90% confidence level) of total SOC change calculations (Gold Standard, Soil organic carbon framework methodology 2020).

13 Discussion

Quantification of different terrestrial carbon stocks and their changes is not a simple task. There is a lot of different scientific research considering different quantification methods, but the comparison of those is hard or even impossible. Each study is designed to give answers to specific research questions, and there is a large variability in used approaches. Different statistical methods, data sources, model choices and scales lead to different accuracy and results. E.g. in soil sampling the sampling depth varies, which hampers the comparison of results. The need for systematic comparison of different quantification methods is high and it should be done to provide information for developing carbon offsetting markets.

Because the accuracy of the quantification methods could not be estimated, all methods were seen possible for carbon offsetting purposes and none was excluded. Cost of carbon stock quantification depends on the accuracy, size of the area under focus and frequency of the measures. The accuracy of carbon stock quantification must be estimated for coming carbon offsetting projects. Open questions in addition to the above are who will pay the measuring costs and what would be the value of carbon credit. All this needs to be solved.

13.1 Forest field measurements

Measuring plant biomass directly is a destructive method and it can't be used to quantify the biomass carbon stock size for carbon offsetting purposes. Typically forest biomass can be estimated with inventory-based approach where field measurements, like tree's height and diameter at breast height, are taken from a certain sampling point and with allometry those values can be converted to biomass estimations (Husch et al. 2003). Forest inventories are conducted in several countries (Tomppo 2014) and there is already large database about forest biomass estimations available. All forest inventories don't include all carbon stocks, and it would be necessary to modify inventories so that all significant pools are included (Birdsey et al. 2013).

Tree biomass can be calculated with allometric relationships which connect some tree characteristics to others resulting an estimation of total biomass (Birdsey et al. 2013). Allometric equations vary widely and each describe certain relationships. Relationships between measured values and other tree measures vary depending on the species (Pearson et al. 2007). Thus, selecting the right equations is essential to produce accurate estimations.

Total biomass carbon quantity estimation in forest, based on inventory, is time consuming and laborious (Berenguer et al. 2015). Sampling design and field work should be well planned so that the results are representative or the whole population under interest (Husch et al. 2003). The cost of inventory approach depends on the accuracy wanted. Many sampling points are needed to reach high accuracy. Carbon stock size that can be estimated from forest inventories is usually presented as Mg C/ha. Inventory where all biomass carbon pools are measured (height and diameter) and tree species are identified (100% inventory), the sampling error is low, almost zero, but the cots is high (Berenguer et al. 2015). There is no common agreement which sampling design would be the most cost-efficient in certain areas and purposes.

Because national forest inventories are representing large areas, it is difficult to down scale the statistically derived information (Husch et al. 2003). When measures from an intensive field sampling is scaled up to larger areas, the estimation is based on the probability (Tomppo 2014). Down scaling from areal estimates to plot level can lead to biases because the smaller area might not be representative to the whole area.

13.2 Remote sensing of aboveground biomass

Remote sensing of aboveground biomass is not an accurate method for carbon offsetting (Issa et al. 2020). Remote sensing can provide valuable information about large scale changes and it can be used to monitor projects (Main-Knorn et al. 2011), but currently sensors are not developed enough for accurate carbon stock estimations.

Optical sensors have wide global coverage and good temporal resolution (French 2013, Holopainen 2019), but they are not sensitive enough to measure biomass variations and their accuracy is not enough for carbon stock estimations (Issa et al. 2020). Radar sensors

can give more information from forest canopies than optical sensors, and they can penetrate clouds (Zolkos et al. 2012), which helps to overcome some application problems. Radar approach is costly and sensor's ability to map high density biomass forest is limited (Zolkos et al. 2012). Radar is not currently accurate enough for carbon stock estimations and it's expensive (Issa et al. 2020). Light detecting and ranging (lidar) is used in small scale forest mappings from ground or from air, but there is still need for satellite based lidar (Sun et al. 2019b). Ground based lidar produces three-dimensional information about stands and it can be used to provide information e.g. from tree height more accurately than conventional field measurements (Holopainen 2019). This would help to build new, more accurate models.

Combining different methods of remot sensingcould increase the accuracy and help to tackle challenges related to a specific sensor type (Issa et al. 2020). To choose the right sensor type, prediction model and combination of all those need considerations which only highly trained expertise are capable to do. There is no common agreement from methodology to be used and each study is implemented separately, which makes the comparison of results difficult and hampers the development of commonly accepted carbon sequestration quantifications (Issa et al. 2020). Overall, the remote sensing techniques need more development to be able to be utilized in carbon offsetting projects.

13.3 Soil sampling

Conventional soil sampling is a direct method of organic soil carbon quantity determination. Because the soil organic carbon quantity varies horizontally and vertically (soil profile) the sampling design needs careful consideration (FAO 2019). SOC is accumulated differently through soil profile (Jobbagy and Jackson 2000) which causes the variation in one-point sample and is the cause why soil samples should be taken in several depths. The sampling depth is still under debate, and there is no common consensus. Soils vary greatly also horizontally and thus the soil sample taken from one point don't necessarily represent the same SOC quantity in 10 cm apart. Because of this variation soil samples should be also taken from several different points (Schrumpf et al. 2011). The number of adequate samples is dependent on the purpose of the sampling, and to determine the total soil carbon quantity in one area (e.g. g C/m^2 or Mg C/ha) the soil

samples should capture the variation in SOC quantity in different layers and places and be as representative as possible (Mäkipää et al. 2008).

To achieve high accuracy and precision the number of needed samples is high (Mäkipää et al. 2008), and the needed number depends on the soil characteristics. Cost of soil sampling depends on the wanted accuracy. Soil sampling is time consuming and laborious, which affects the costs. Costs vary greatly between projects.

Soil is not a homogenous matter and it includes different components in different sizes, like gravel, stones, water and air. Due to the fact that different soil types include different number of factors mentioned (e.g. water), the SOC quantity should be presented in equivalent soil mass (FAO 2019). Dry bulk density is important to take into consideration because if next sampling is conducted after soil compaction the carbon quantity would be higher in the same volume due to the loss of air pores and not necessarily due to the increase in soil organic carbon quantity (FAO 2019). Errors in bulk density determinations can lead to significant errors in total carbon quantity.

Soil sampling can be conducted in all soil types, in a small scale. If sampling is conducted only for small scale, the results are difficult to scale up to larger areas (Goidts et al. 2009). Scaling decision depends on how statistically representative the few samples are. If landscape is homogenous and managed, the variation could be small, and scaling could be done to larger areas with possible smaller biases. Scaling decision needs knowledge of soil type, history, topography, carbon inputs and climate and their affect to soil organic carbon (Vanguelova et al 2016).

Soil sampling is not an effective quantification method for carbon offsetting because the "background" soil carbon stock is large, the annual soil organic carbon stock change is small, and the soils are very heterogeneous (Peltoniemi et al. 2004). Soil sampling is still needed for to increase knowledge of soil carbon dynamics under different management practices under different climates, so that carbon sequestration can be better understood (Saarsalmi et al. 2014).

13.4 Modelling soil carbon

Simulation of carbon stocks and carbon stock changes with different models is a widely used approach. Model simulations are usually performed to provide information from the effect of different practises on the soil carbon turnover rate and accumulation (Paustian et al. 2019). There are several different options to simulate soil carbon turnover. The choice of the model depends on the purpose and data available (Manzoni and Porporatio 2009, FAO 2019). The internal structure and the level of details of different soil carbon models varies (Battle-Aguilar et al. 2011), and there is no common rule to select the model to be used. Input data and data for model evaluation are typical limiting factors affecting model application (Peltoniemi et al. 2007).

Empirical models are usually developed from global datasets (Paustian et al. 2019) and for national carbon stock estimations (FAO 2019) which hampers their application in small scale projects. Process-based models have advantages of detecting soil carbon turnover in detail, but because of that they have also higher data requirements which limits their application. One limiting factor of the use of the process-based models is the fact that most soil organic carbon models are developed for temperate climate (Campbell and Paustian 2015) and therefore they should be validated to other climatic conditions. Generally, can be concluded that locally validated models give the most accurate estimations of carbon stocks (FAO 2019), which means that a lot of data is needed for more accurate simulations in future.

It might not be possible to use one model approach only for all different environments, but one selection criteria for model selection is its general applicability. Models behave differently in different environments and if several models are used to estimate carbon stocks their differences must be known. The internal structure of each model should be known thoroughly so that their performance in varying environments can be evaluated.

13.5 Proximal soil sensing

Soil carbon quantity determination with spectroscopic measurements include several approaches. Sensors that sense visible-near infrared and mid-infrared spectral regions are used to measure soil organic carbon quantity in soils (England and Viscarra Rossel 2018).

Especially interesting are approaches that include measurements in field conditions. Measurements made *in situ* would reduce costs and labor requirements, if samples could be measured immediately without transportation to a laboratory. Currently this is not totally possible, due to the calibration requirements (Angelopoulou et al. 2020). Current methods are not accurate enough without extensive calibration and calibration at this state requires sample analysis with a conventional laboratory analysis and developing adequate spectroscopic model according to those samples (Angelopoulou et al. 2020).

Accurate spectroscopic measurements made in laboratory with benchtop devises are intended for dried and homogenized samples. In field conditions natural environment factors like soil moisture and vegetation cover cause uncertainties in spectral measurements (Geht and Rice 2006) because sensors don't specify the source where the reflectance is coming. In field conditions, a rough surface scatters the reflectance differently compared to finely grounded samples (Rodionov et al. 2014). All these factors hamper the application in field conditions.

SOC quantity measurements would be beneficial to do with a device that could be used to gather information from other soil properties simultaneously. This could be used especially in agriculture, where spectroscopic techniques are used for precision farming (Mulla 2013).

Proximal soil sensing can be carried out in several ways, but if the purpose is to determine the soil organic carbon quantity in a certain area, the measurements should be taken from a soil sample cored with auger from a specific depth (England and Viscarra 2018). The dry weight and dry bulk density should also be determined from that sample for carbon quantity estimations. To determine the soil mass and bulk density, the sample should be dried and weighted, and this cannot be done in field conditions only, which is major limitation. Sensing of bulk density is a method under development (England and Viscarra 2018).

In future soil organic carbon content sensors used in field conditions could be laser-induced breakdown spectroscopy and inelastic neutron scattering, but currently both of them are under research and not available (Paustian et al. 2019). Both devices are expensive, and their ability to work in field conditions is not fully understood (Viscarra

Rossel et al. 2011). Inelastic neutron scattering of gamma rays (Wielopolski et al. 2008) is a safety concern if used in fields. This issue needs sever consideration.

13.6 Eddy covariance

Carbon dioxide flux measurements with an eddy covariance is a direct method to estimate the whole ecosystem carbon budget (Baldocchi 2003). When carbon fluxes between soil and atmosphere, and other carbon inputs and outputs are studied, the result can be used to estimate if the ecosystem under interest acts as a carbon sink. This method doesn't detect where the carbon is sequestrated and if it's important to quantify the different carbon stocks separately, soil respiration measurements should be included (Baldocchi 2003). In cultivated lands, the amount of carbon lost (e.g. harvest) and carbon inputs (e.g. manure) affect the whole ecosystem carbon budget and should be considered accordingly. Natural carbon losses from the ecosystem through e.g. leaching and erosion are also sources of error and hard to monitor (Jones et al. 2017).

Eddy covariance is a point in space measurement, and it works best under homogenous landscape with proper wind flow (Aubinet et al. 2012). In natural environments the conditions are not always ideal and thus data needs several corrections. A long measurement time is needed to reduce uncertainties (Flechard e al. 2020). Eddy covariance technique is advanced and complex and for using this technology is needed highly trained expertise to maintain the measurements and to process and analyze the data (Aubinet et al. 2012). Because eddy covariance tower and the measurement method as a whole is expensive (e.g. high expertise salary) and sophisticated (Baldocchi 2003), it is currently used only in research. To be able to utilize carbon flux information for carbon stock change quantification purposes, the towers should be built to intensive measurement areas and provide information gathered from those sites to offset projects. All different land use forms should be covered in different environments. This is of course problematic in agricultural area, because there is a huge variety of crops and management practices, and it would require a large number of measurement points to cover all possible combinations.

Eddy covariance method is not practical for carbon offsetting purposes, but it provides information about how different environmental variables and management practices

effect on carbon fluxes at the whole ecosystem level. That information can be used for example for model development (Paustian et al. 2019). Long term flux measurements from different land use areas would provide valuable information for future quantification method applications and estimations of carbon sequestration potential.

14 Conclusions

Methods for terrestrial carbon pool quantification are dependent on high quality data. To increase the accuracy of quantification methods empirical research should provide information needed to fill information gaps and to reduce uncertainties in estimation. For carbon offsetting purposes of carbon markets, the quantification method should be achievable, cost efficient, repeatable and transparent. Aboveground carbon stock estimations can be achieved more effectively than underground estimations, but the main interest is in soil organic carbon and underground biomass carbon stock. At this moment simulation of stock change is the most achievable approach and it could be used in carbon offsetting projects, if the method gains a common acceptance. To achieve that, the modelling method should be based on science, the good quality data should be available and there should be evidence that simulations result the real carbon stock with acceptable accuracy. Increasing knowledge of soil processes and data collected from different sources helps to develop models further and decreases the uncertainty of results. At this state, the developing carbon market needs cost-effective approach to include small scale projects and to increase the supply of creditable carbon units. To increase the overall knowledge of carbon sequestration and to improve quantification methods a long-term research projects and co-operation between different method developments are needed.

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